New Applications of Data Assimilation to Climate Systems: Correcting the model biases based on Analysis Increments, Proactive QC, Strongly Coupled Data Assimilation.

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T. Miyoshi, G.-Y. Lien, (RIKEN), S.-C. Yang, (CTU), D. Hotta & Y. Ota (JMA), J.-S. Kang (KIAPS), Fanglin Yang (EMC)
with many thanks to students, friends and colleagues
from the University of Maryland

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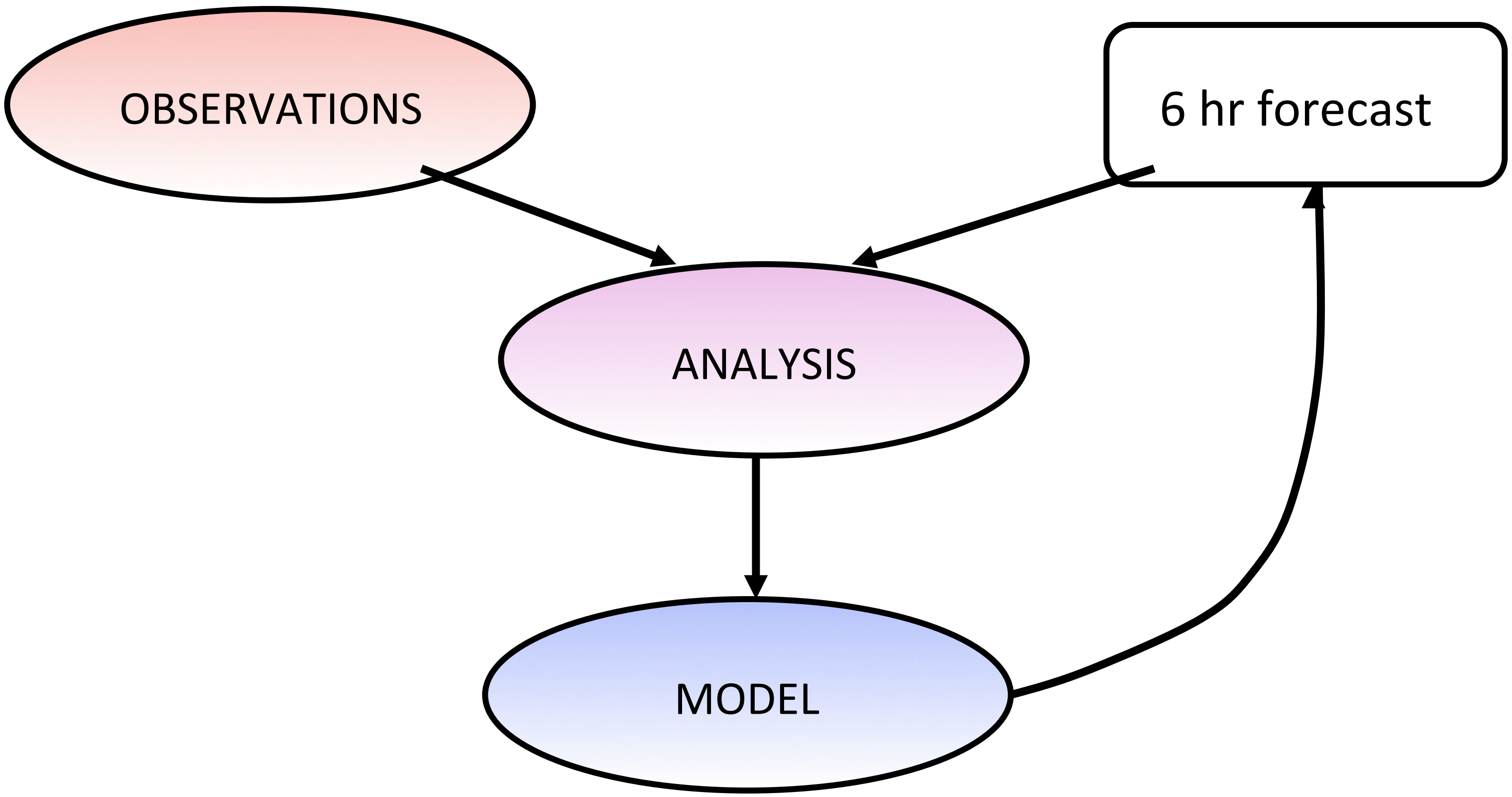
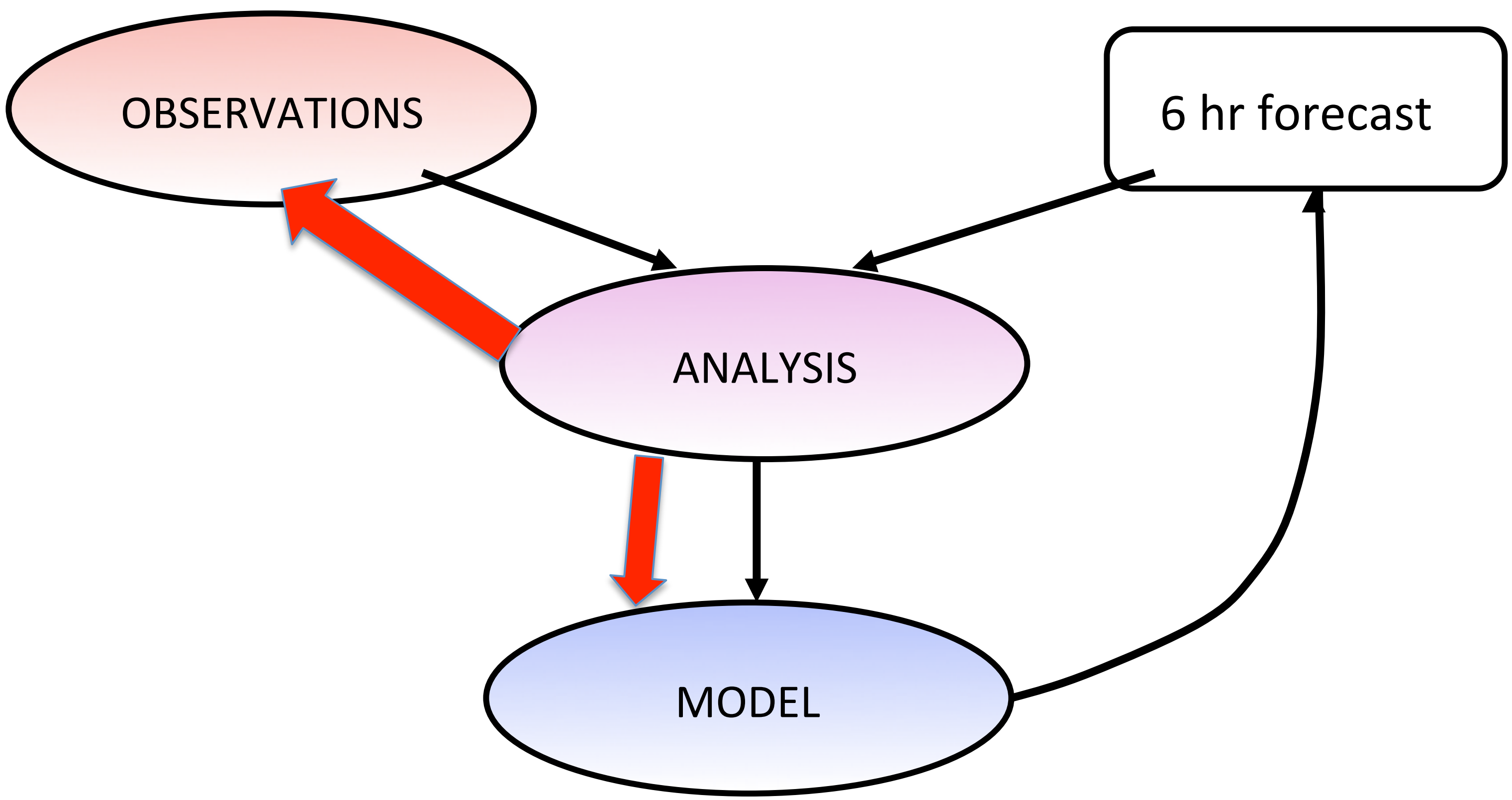
Classic Data Assimilation: For NWP we need to improve observations, analysis scheme and model



New Data Assimilation: We can also use DA to improve observations and model



The simplicity and power of EnKF should encourage the use of DA for improvements beyond its main goal

Combine optimally observations and model forecasts

- We should also use DA to:

  2) Improve the observations

  3) Improve the model

- Also, do more truly coupled DA:

  4) Example: The ocean and the atmosphere are coupled: obviously the best DA should be coupled

- Currently the Earth System models used by IPCC for climate change do not predict population, they obtain it from UN projections.

  5) We should do DA of the coupled Earth System-Human System

The simplicity and power of EnKF should encourage the use of DA for improvements beyond its main goal

Combine optimally observations and model forecasts (mostly done!) ☺

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The simplicity and power of EnKF should encourage the use of DA for improvements beyond its main goal, namely

Combine optimally observations and model forecasts

- We should also use DA to:

Improve the observations: PQC, nice results

Improve the model: Use analysis increments

- Also, do more truly coupled DA:

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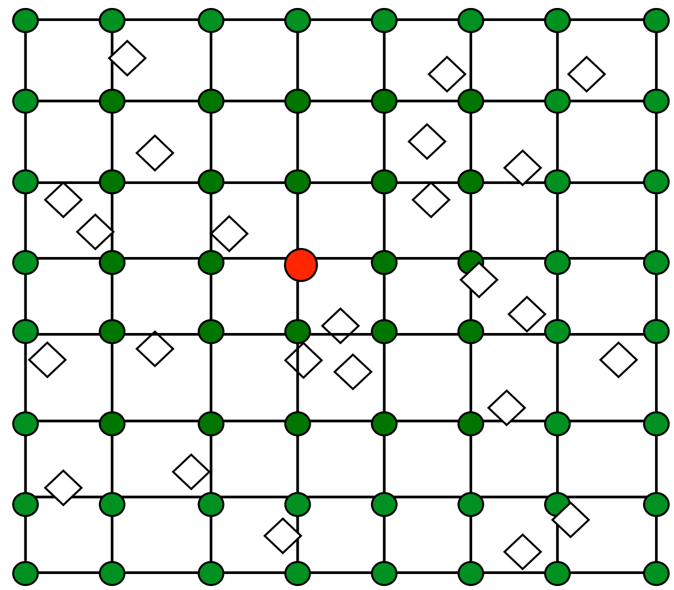
- **We should do DA of the coupled Earth System-Human System**

LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot

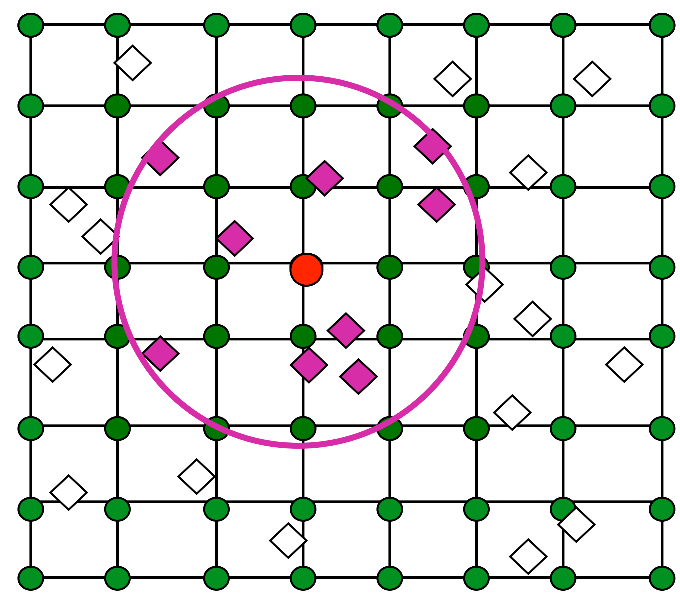


LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot

All observations (purple diamonds) within the local region are assimilated



The LETKF algorithm can be described in a single slide!

Local Ensemble Transform Kalman Filter (LETKF)

Globally:

Forecast step: $\mathbf{x}^b_{n,k} = M_n\left(\mathbf{x}^a_{n-1,k}\right)$

Analysis step: construct $\mathbf{X}^b = \left[\mathbf{x}^b_1 - \overline{\mathbf{x}}^b \mid \ldots \mid \mathbf{x}^b_K - \overline{\mathbf{x}}^b\right];$

$$\mathbf{y}^b_i = H(\mathbf{x}^b_i);\ \mathbf{Y}^b_n = \left[\mathbf{y}^b_1 - \overline{\mathbf{y}}^b \mid \ldots \mid \mathbf{y}^b_K - \overline{\mathbf{y}}^b\right]$$

Locally: **Choose for each grid point the observations to be used, and compute the local analysis error covariance and perturbations in ensemble space:**

$$\tilde{\mathbf{P}}^a = \left[(K-1)\mathbf{I} + \mathbf{Y}^T\mathbf{R}^{-1}\mathbf{Y}\right]^{-1};\ \mathbf{W}^a = [(K-1)\tilde{\mathbf{P}}^a]^{1/2}$$

Analysis mean in ensemble space: $\overline{\mathbf{w}}^a = \tilde{\mathbf{P}}^a\mathbf{Y}^{bT}\mathbf{R}^{-1}(\mathbf{y}^o - \overline{\mathbf{y}}^b)$

and add to $\mathbf{W}^a$ **to get the analysis ensemble in ensemble space.**

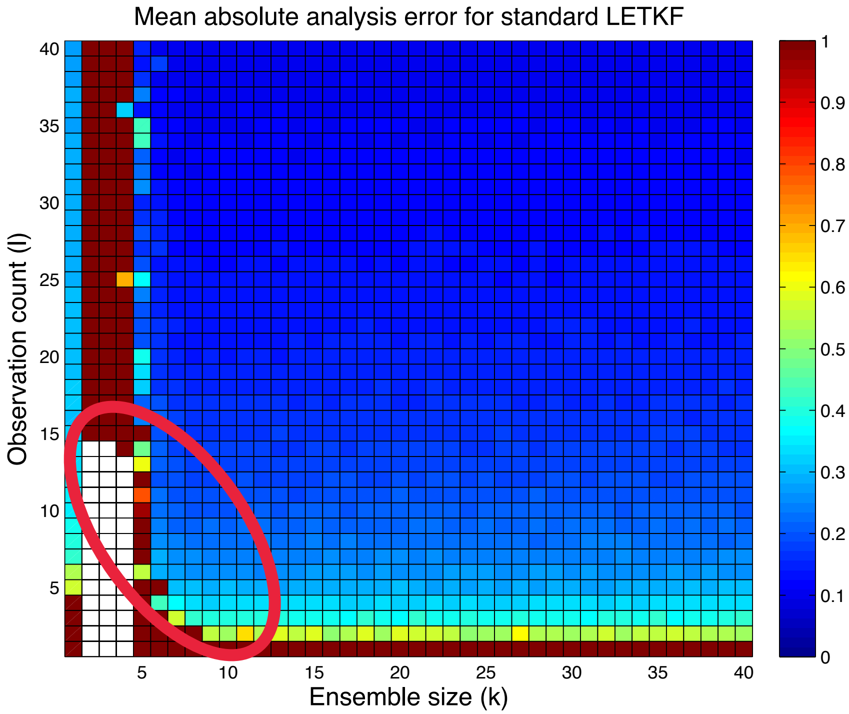
The new ensemble analyses in model space are the columns of $\mathbf{X}^a_n = \mathbf{X}^b_n\mathbf{W}^a + \overline{\mathbf{x}}^b$. **Gathering the grid point analyses forms the new global analyses. Note that the the output of the LETKF are analysis weights** $\overline{\mathbf{w}}^a$ **and perturbation analysis matrices of weights** $\mathbf{W}^a$. **These weights multiply the ensemble forecasts.**

Hybrids between Var and EnKF

- So far **Covariance-Hybrids** have been used, combining an existing Var system with an ensemble that provides the flow dependence of the background error covariance.
- Penny (2014) developed a **Gain-Hybrid**, very simple to implement, that starts with the LETKF analysis and adds a Var analysis. ECMWF tested it with excellent results (Hamrud et al. 2014, TM733).
- The LETKF analysis is used as first guess by the Var, and the analysis is αVar+(1- α)LETKF + (LETKF perturbs).
- Penny tested it with the Lorenz 96 model: The analysis error is plotted as a function of the number of ensemble members (2 to 40) and the number of observations (1 to 40).
- Student Matthew Wespetal tested it on the SPEEDY global atmospheric model with the LETKF coupled with 3D-Var.

Gain-Hybrid with a simple local 3D-Var (Penny, MWR2014) applied to the Lorenz 96 model

Standard LETKF



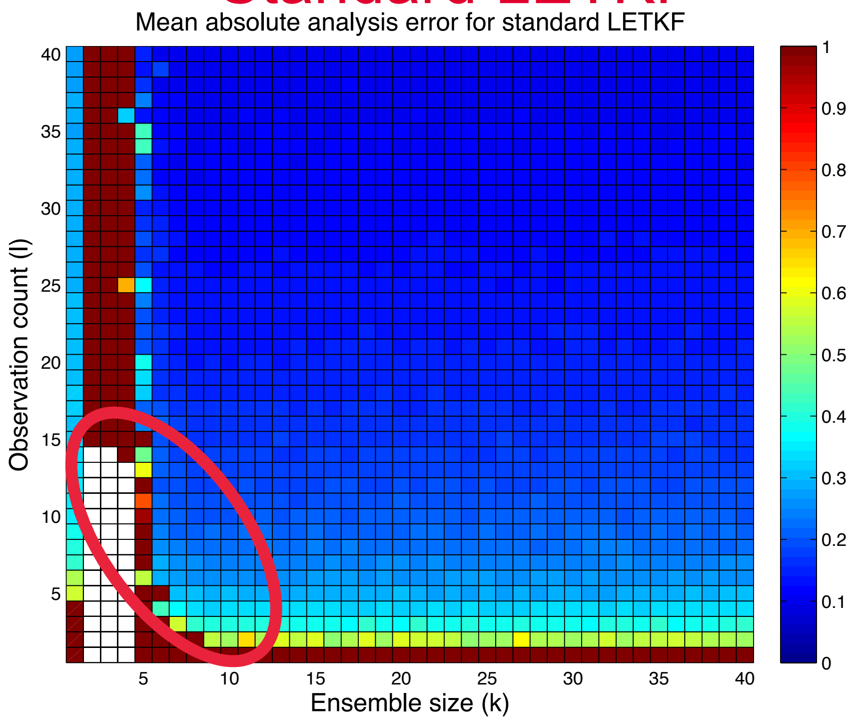
This is the corner where we are in ocean EnKF: too few obs, too few ensembles

The total model dimension is K=40

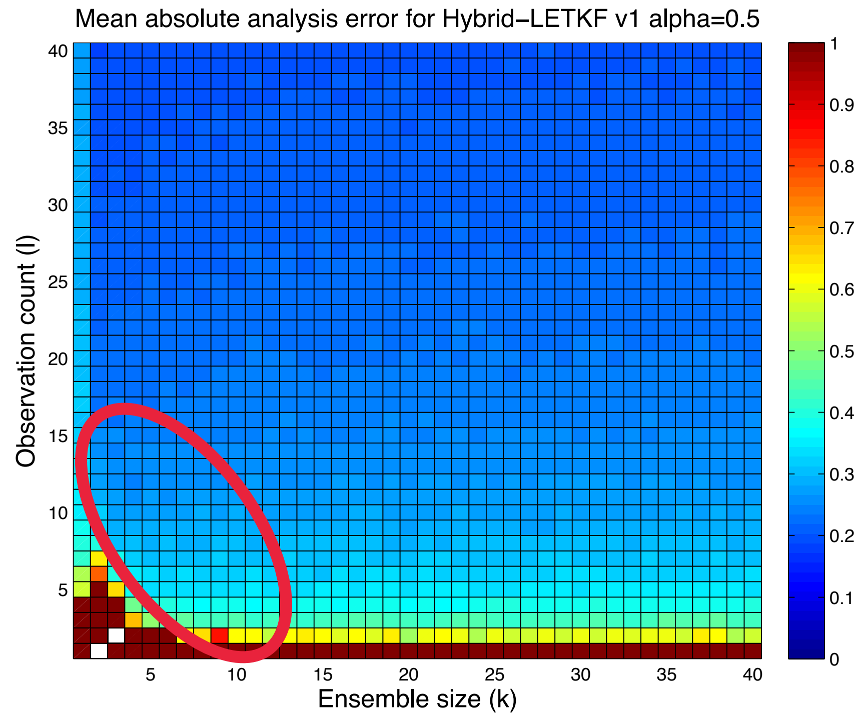
The LETKF is extremely accurate as long as k>7, number of obs>7.

Gain-Hybrid with a simple local 3D-Var (Penny, MWR2014) applied to the Lorenz 96 model

Standard LETKF



Add a simple 3D-Var to LETKF



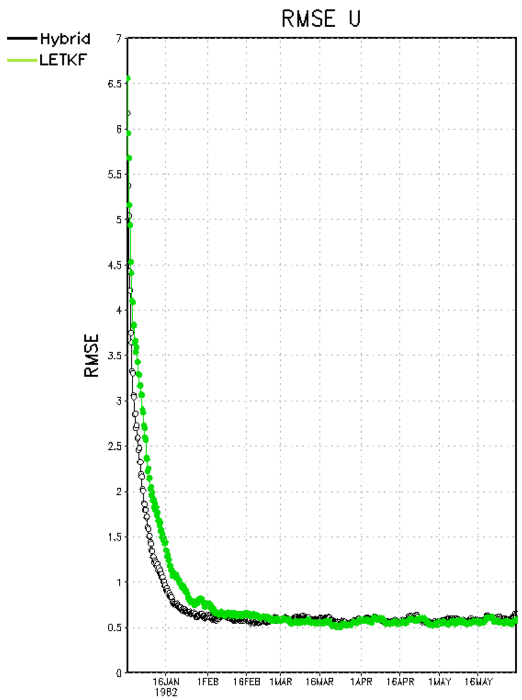
The hybrid LETKF- 3D-Var is more robust for few ensemble members and few observations, as in the ocean.

ECMWF implemented Penny's Gain-Hybrid with excellent results, even slightly better than their operational EDA

LETKF and Hybrid on the SPEEDY model

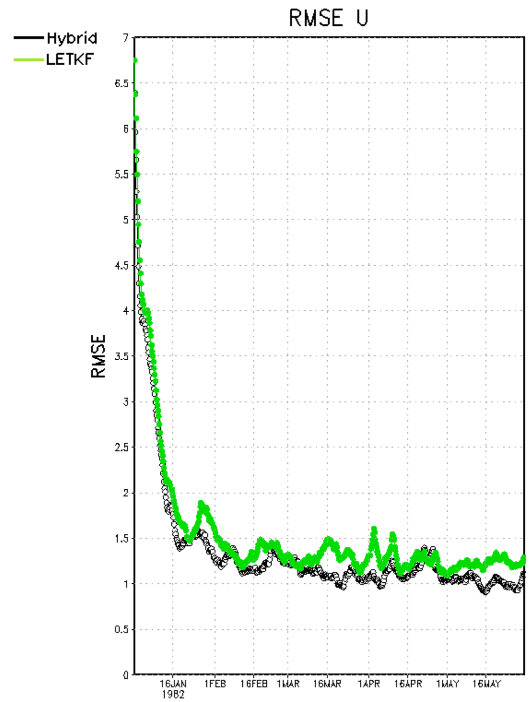
Hybrid vs LETKF (20 members) RMSE

- **satellite + rawinsondes**
- alpha = 0.5



rawinsondes only

alpha = 0.5



As expected, for the **data rich case**, the hybrid converges faster but becomes slightly worse than the LETKF.

For the **data poor case**, the **hybrid is better** than the pure LETKF.

(from Matthew Wespetal).

Traditional approaches to coupling

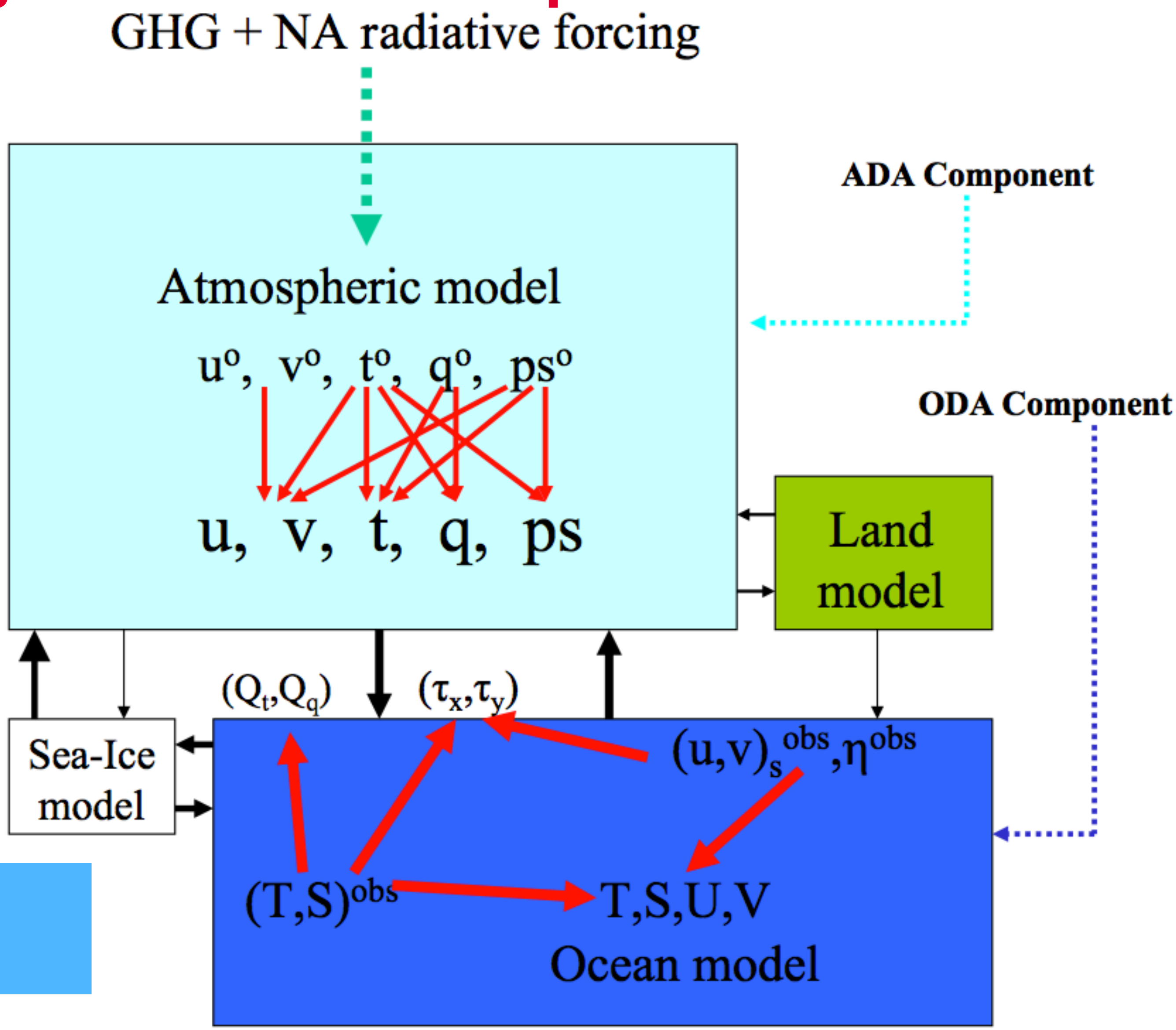
- In a typical coupling scheme for an ocean-atmosphere **model**, the ocean model passes SST to the atmosphere, while the atmosphere passes back heat flux components, freshwater flux, and horizontal momentum fluxes. (Neelin, Latif & Jin, 1994)
- In standard data assimilation, atmospheric observations are assimilated only by the atmospheric model, and ocean observations are assimilated only by the ocean. We call this **weak** (or standard) coupling.
- SST in the ocean model is frequently nudged from “Reynolds (OI) SSTs”, not assimilated from observations.
- SSH and Salinity may not be even be used.
- The data assimilation windows for the ocean are much longer than for the atmosphere.
- We introduce the concept of strongly coupled data assimilation.

How to do coupled ocean-atmosphere data assimilation?

- Should we do coupled data assimilation?
- Yes! e.g., see Tamara Singleton thesis
- Current approaches assimilate separately the ocean and the atmosphere, and then couple the models (weak coupling)
- We propose strong coupling: the ocean sees the atmospheric observations, and the atmosphere sees the ocean observations (Sluka, Penny, Miyoshi)

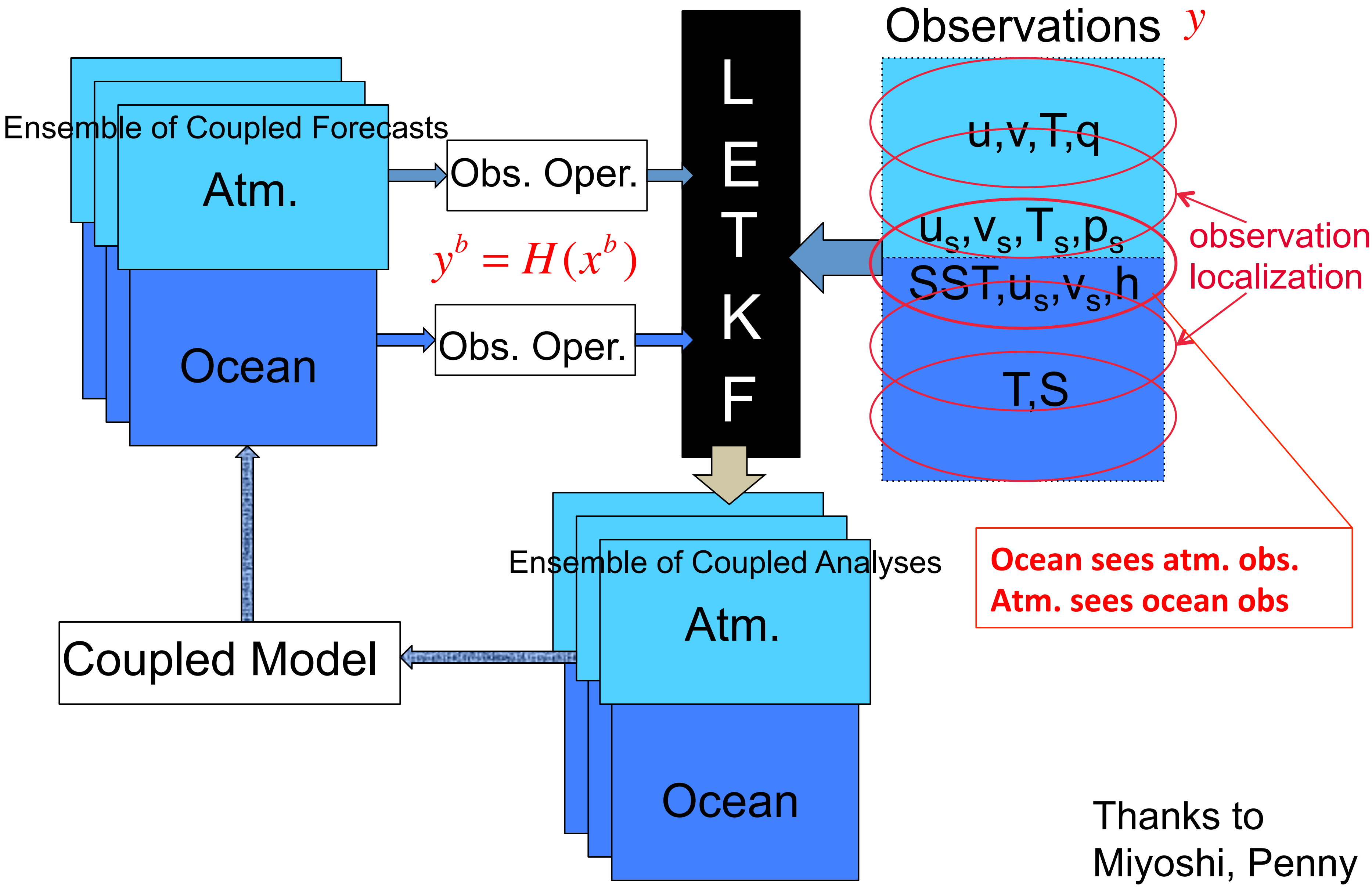
Data Assimilation: STANDARD (WEAK) COUPLING
S. Zhang et al.: GFDL Coupled Ocean-Atm EnKF

Atmosphere assimilates only atm. obs.!



Ocean assimilates only ocean obs.!

Our strongly coupled LETKF assimilation



Thanks to
Miyoshi, Penny

Impact of strong coupling of the ocean-atmosphere LETKF (Travis Sluka)

- **SPEEDY-NEMO** coupled model. Perfect model OSSE.
- Standard (weak) coupling as a control
- Test strong coupling: the ocean sees the atmospheric observations and the atmosphere sees the ocean observations

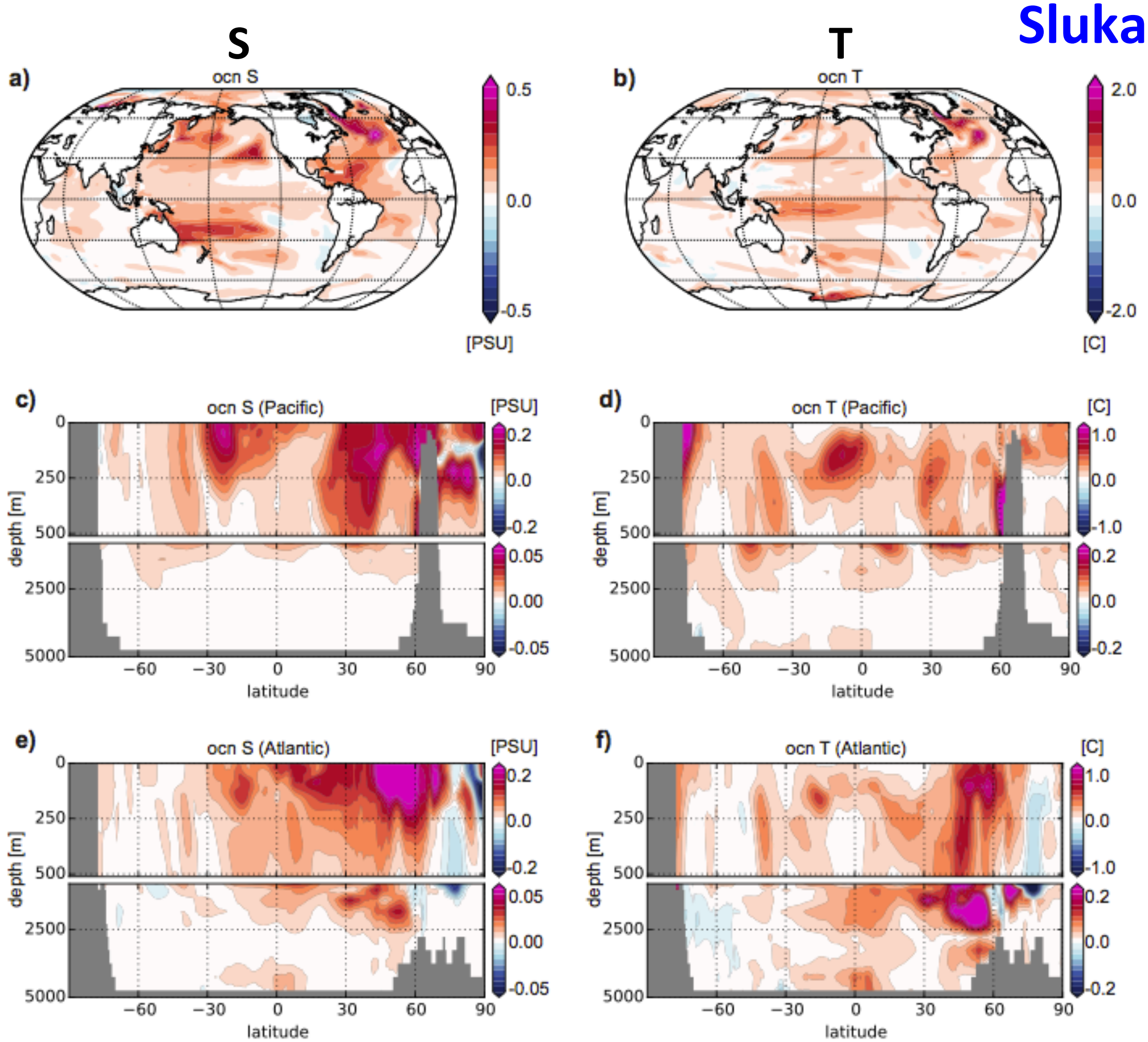
Experiments: 1) Only atmos. obs.

(2) Only ocean obs.)

- CONTROL: Weakly coupled data assimilation: Only the atmosphere assimilates atmos. observations.
- Strongly coupled DA: ocean also assimilates atmospheric observations (and vice versa).

Results: Red means STRONG DA is better!

Sluka et al., in preparation

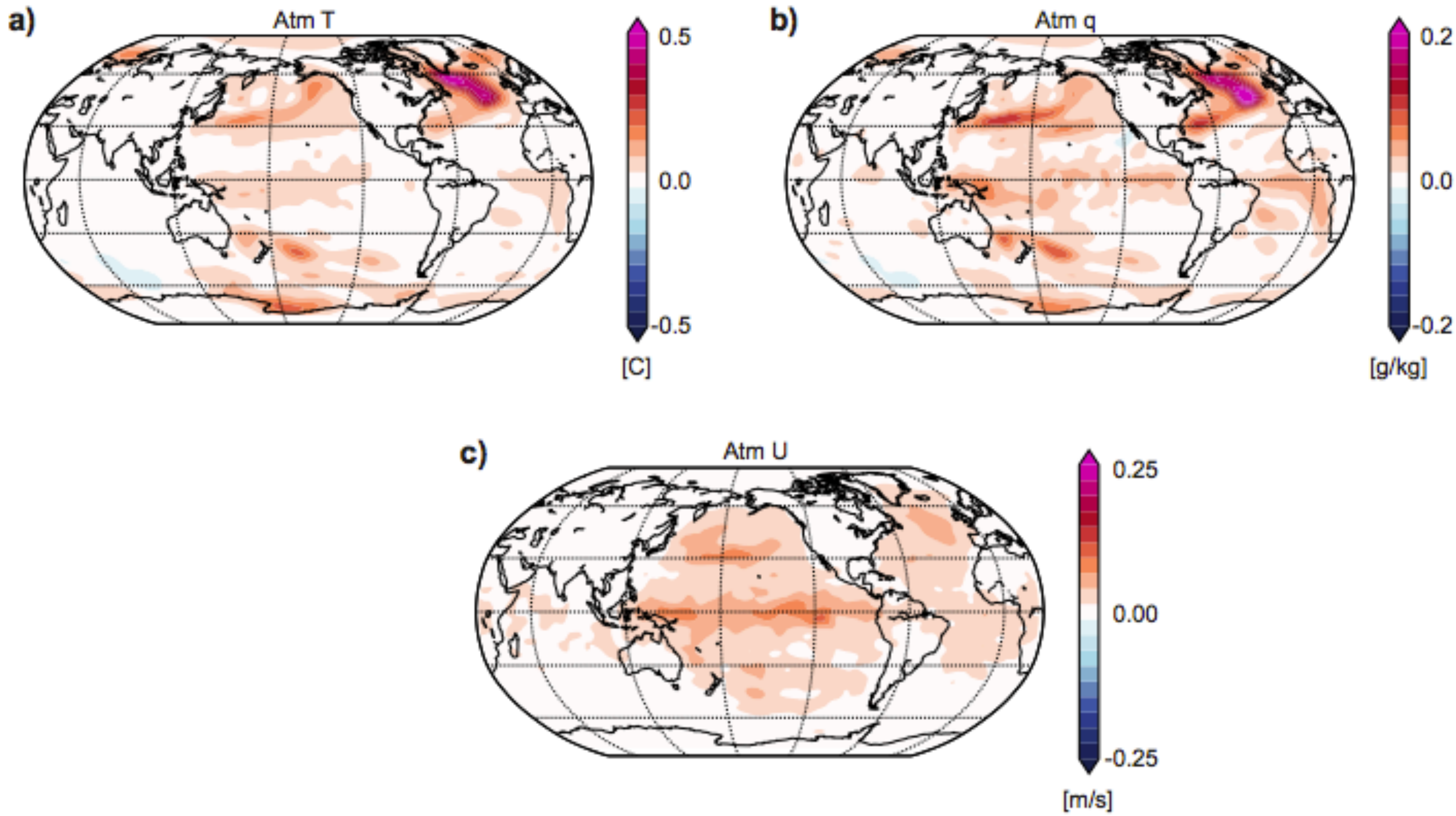


- With Strongly Coupled DA, the errors in temperature and salinity decrease by about 50%.
- The improvements reach the lower levels.

Results: Red means STRONG DA is better!

Sluka et al., in preparation

In turn, with Strongly Coupled DA, **the ocean improved by assimilating atmospheric observations improves the atmosphere**!



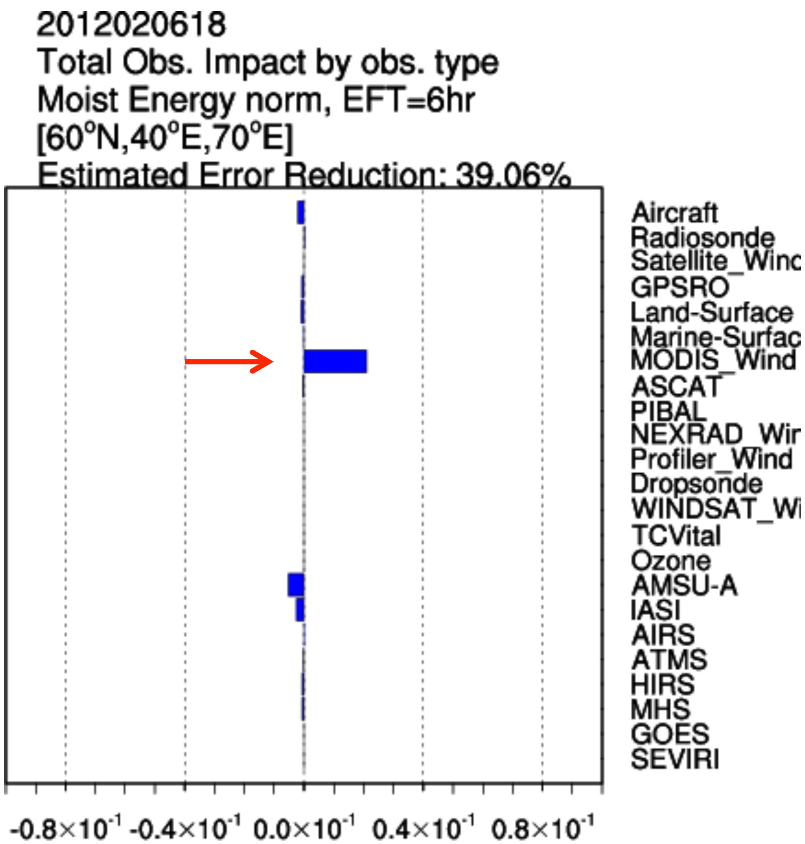
Improve the observations: Ensemble Forecast Sensitivity to Observations and Proactive QC

- Kalnay et al. (2012) derived EFSO.
- Ota et al. (2013) tested 24hr forecasts and showed EFSO could be used to identify bad obs.
- D. Hotta (2014): EFSO can be used after only 6 hours, so that the bad obs. can be withdrawn and collected with useful metadata so they can be improved.
- We call this **Proactive QC**, much stronger than QC.
- Hotta also showed EFSO can be used to tune **R**
- Tse-Chun Chen (2015) tested impact of EFSO/PQC over 5 day forecasts: **NEW RESULTS!**

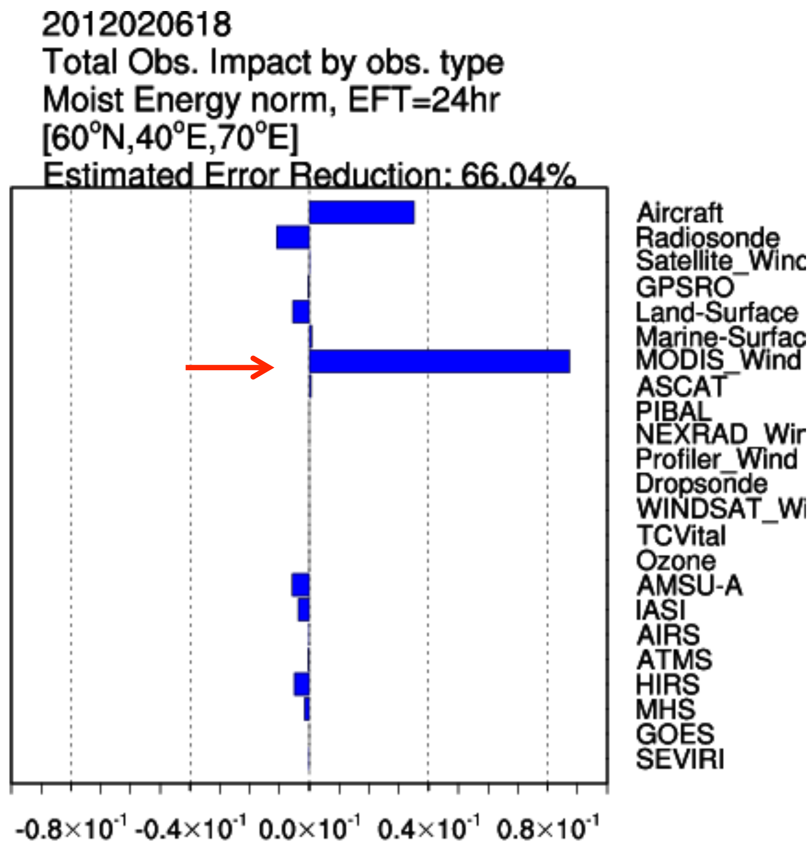
Hotta (2014)

Feb. 18 06UTC, near the North Pole
(Ota et al. 2013 case). Bad obs: MODIS WIND

FT=06 hr.



FT=24 hr.

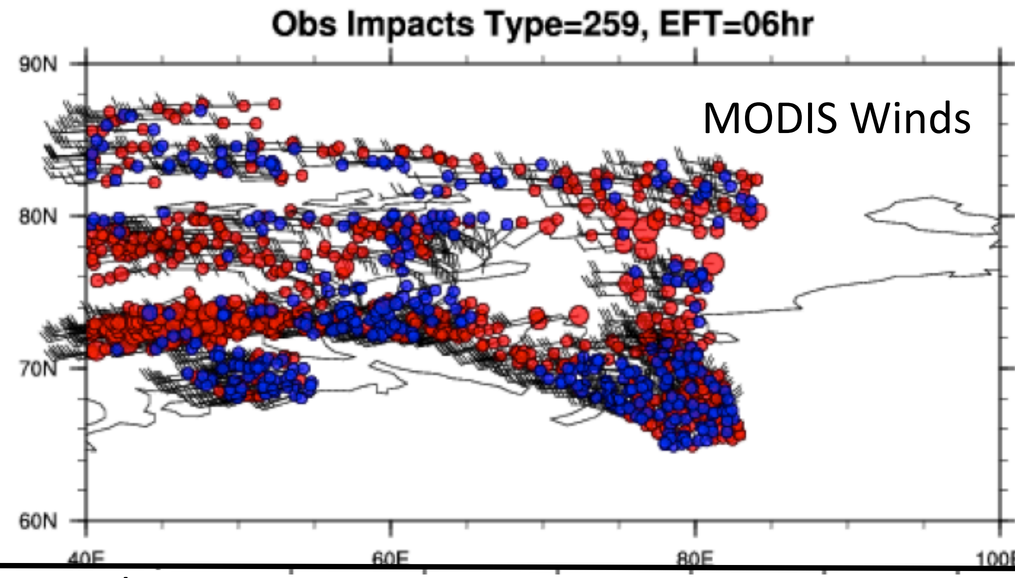


Can identify the bad observations after only 6 hours!

Improve observations:

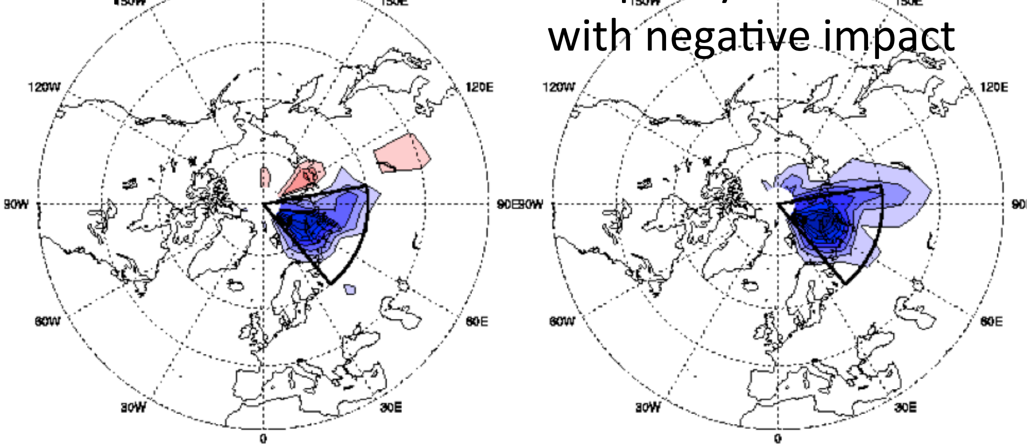
Proactive QC: Find and delete the obs that make the 6hr forecast worse using EFSO

Dr. Daisuke Hotta (2014):
EFSO is able to find whether <u>each</u> observation improves (blue) or makes the 6hr forecast worse (red)



Drop all MODIS winds

Drop only MODIS winds with negative impact



Impact of 6hr PQC on 24hr fcst

PQC with metadata can be used to improve the algorithm!

It should accelerate optimal assimilation of new instruments!

Implementation to the real operational system (2) can we afford to do analysis twice?

Idea: Use **approximated analysis** rather than doing analysis again:

- Using the approximation to Kalman gain:

$$\mathbf{K} \approx \frac{1}{K-1}\mathbf{X}_0^a\mathbf{X}_0^{aT}\mathbf{H}^T\mathbf{R}^{-1} \approx \frac{1}{K-1}\mathbf{X}_0^a\mathbf{Y}_0^{aT}\mathbf{R}^{-1}$$

  the change in analysis by the denial of observations can be approximated by:

$$\bar{\mathbf{x}}_0^{a,\mathrm{deny}} - \bar{\mathbf{x}}_0^a \approx -\mathbf{K}\delta\bar{\mathbf{y}}_0^{ob,\mathrm{deny}} \approx -\frac{1}{K-1}\mathbf{X}_0^a\mathbf{Y}_0^{aT}\mathbf{R}^{-1}\delta\bar{\mathbf{y}}_0^{ob,\mathrm{deny}}$$

- As inexpensive as EFSO.

→ **No need to repeat analysis**

→ Can minimize the time delay

Can be used to tune **R**! (Hotta, 2014)

Ensemble Forecast Sensitivity to **Error Covariances**

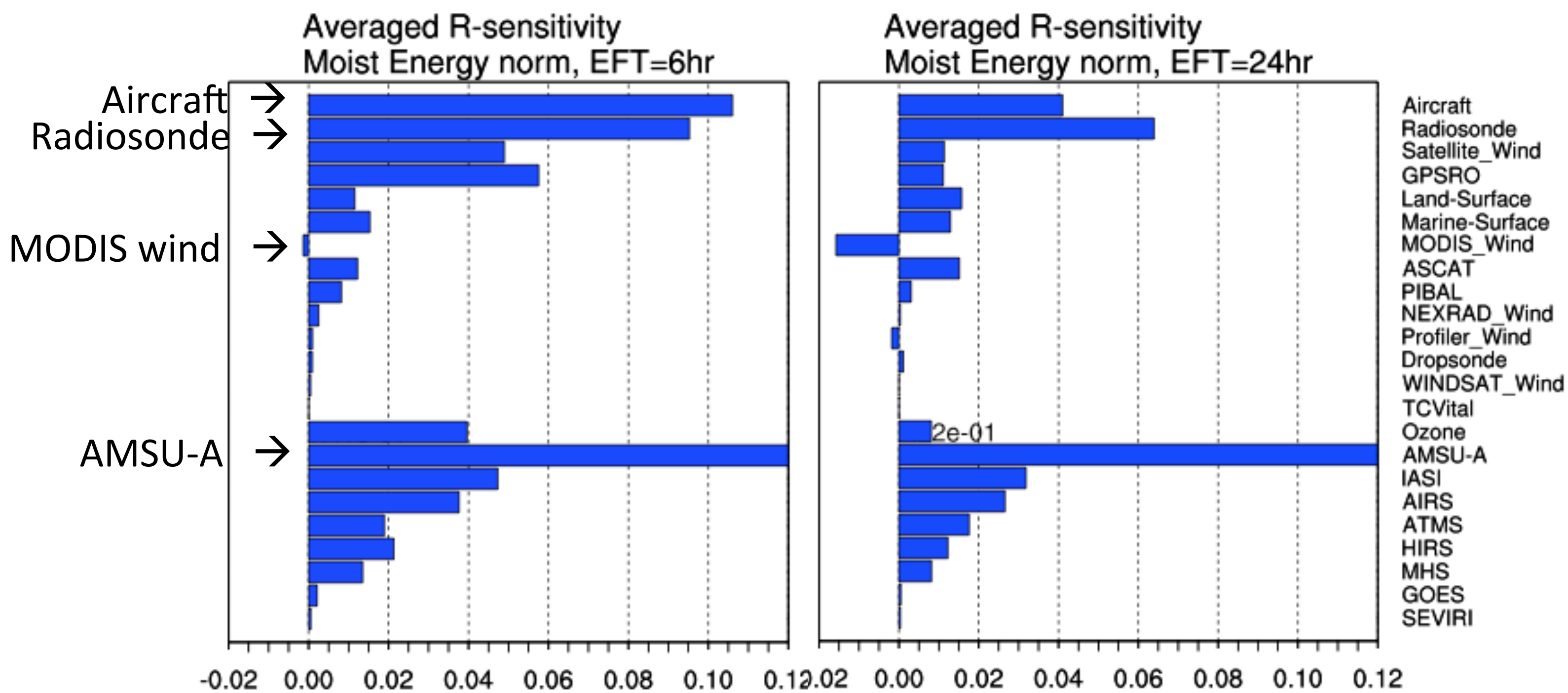
Hotta (2014)

- Daescu and Langland (2013, *QJRMS*) proposed an adjoint-based formulation of forecast sensitivity to **B** and **R** matrix.
- Daisuke Hotta formulated its ensemble equivalent for **R** using **EFSO** by Kalnay et al. (2012) :

$$\left[\frac{\partial e}{\partial \mathbf{R}}\right]_{ij} \approx \frac{\partial e}{\partial y_i} z_j \approx -\frac{1}{K-1}\left[\mathbf{R}^{-1}\mathbf{Y_0^a}\mathbf{X_{t|0}^{fT}}\mathbf{C}\left(\mathbf{e_{t|0}} + \mathbf{e_{t|-6}}\right)\right]_i \left[\mathbf{R}^{-1}\delta y^{oa}\right]_j$$

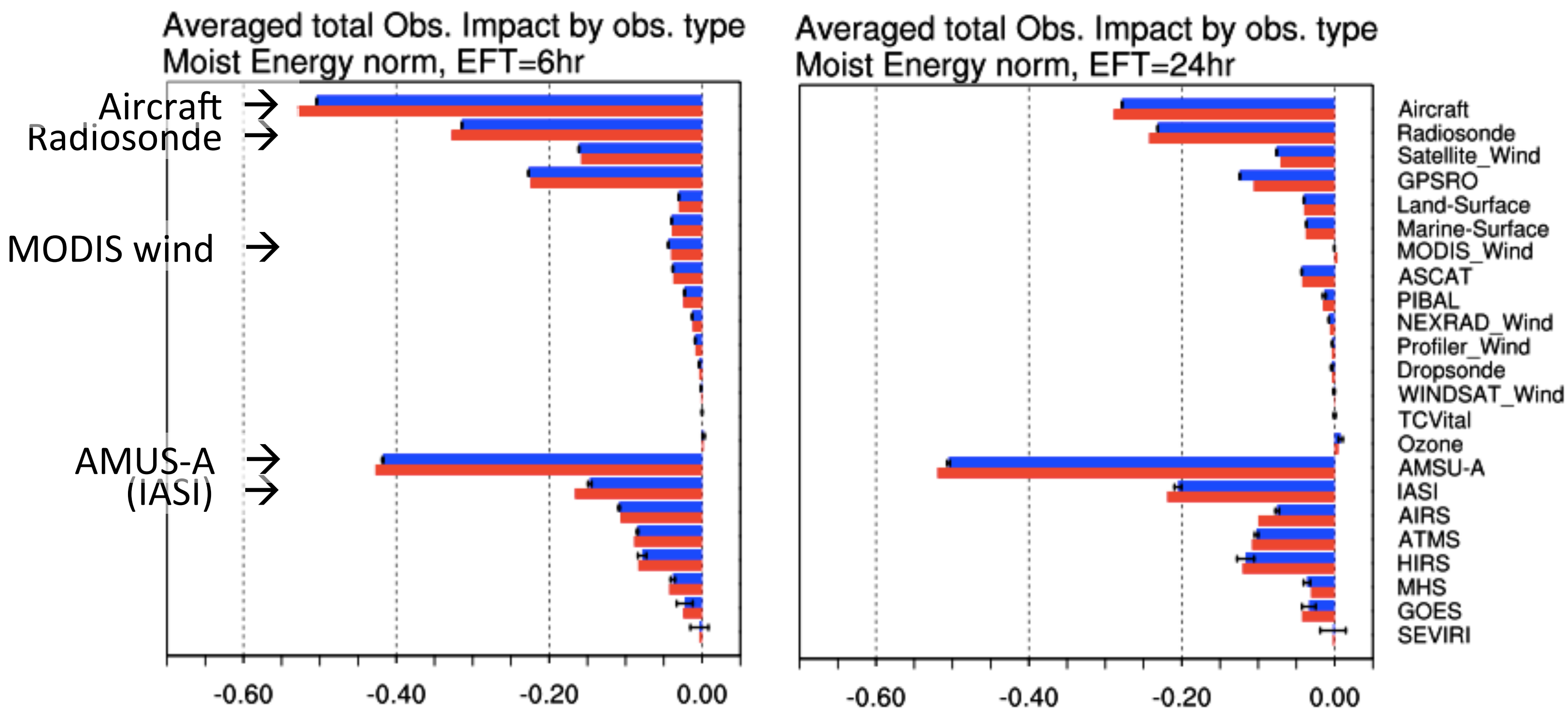
where $\mathbf{z}$ is an "intermediate analysis increment" in observation space

R-sensitivity results from GFS / GSI-LETKF hybrid



- Positive value: error increases as s_o^2 increases → should decrease s_o^2
- Aircraft, Radiosonde and AMSU-A: large positive sensitivity
- MODIS wind : negative sensitivity
- → **Tuning experiment**:
  - Aircraft, Radiosonde and AMSU-A: scale s_o^2 by 0.9
  - MODIS wind: scale s_o^2 by 1.1

Tuning Experiment: Result
EFSO before/after tuning of R

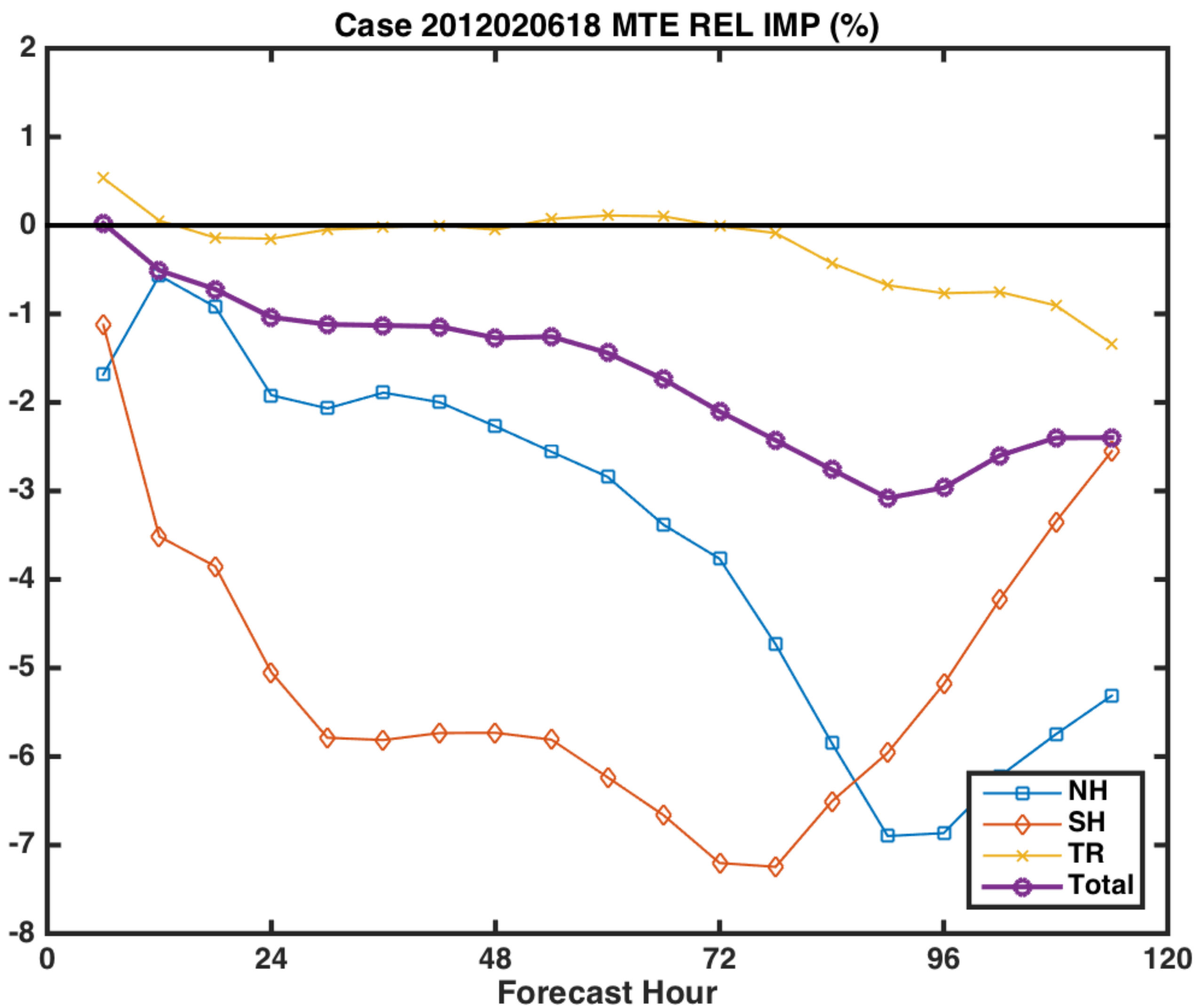


- Aircraft, Radiosonde and AMSU-A: significant improvement of EFSO-impact
- MODIS wind : insignificant difference in EFSO
- IASI: Significant improvement in EFSO although its error covariance is untouched!

Current testing of PQC on JCSDA S4
Tse-Chun Chen

- Before operational testing, we need to show that:
  - Denying flawed observations improves the forecasts.
  - Denying flawed observations works in a cycled way (we tested case by case so far).
  - The EFSO approximation (constant K) can be used to replace the full analysis without the flawed observations (much faster).
  - We can use the 6hr early forecast to check the final analysis.
- Prof. Daryl Kleist has kindly offered to help test PQC operationally once we have good results.
- So, let's look at the results: We tested 9 cases of withdrawing flawed observations, re-computing the analysis and performing 5-day forecasts with and without the flawed observations.

Results: we measure the % change in forecast error (Moist Total Energy) when withdrawing flawed obs.



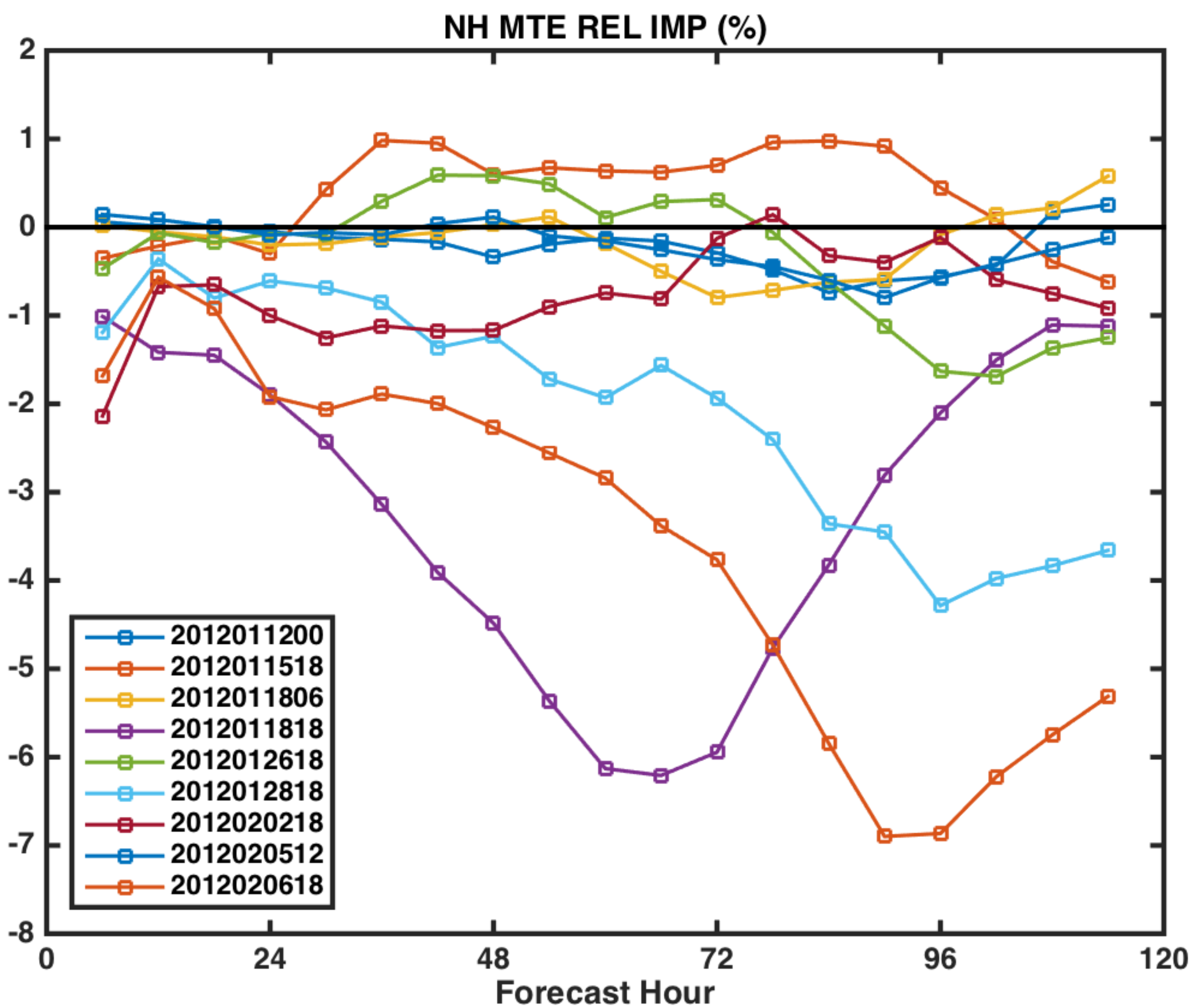
BEST CASE

Flawed obs in both NH and SH

7% reduction of error in both NH and SH! ("Skill-dropouts")

Random changes increase initial errors in the tropics, but the tropics also improve with time.

All 9 cases: impact in NH extratropics

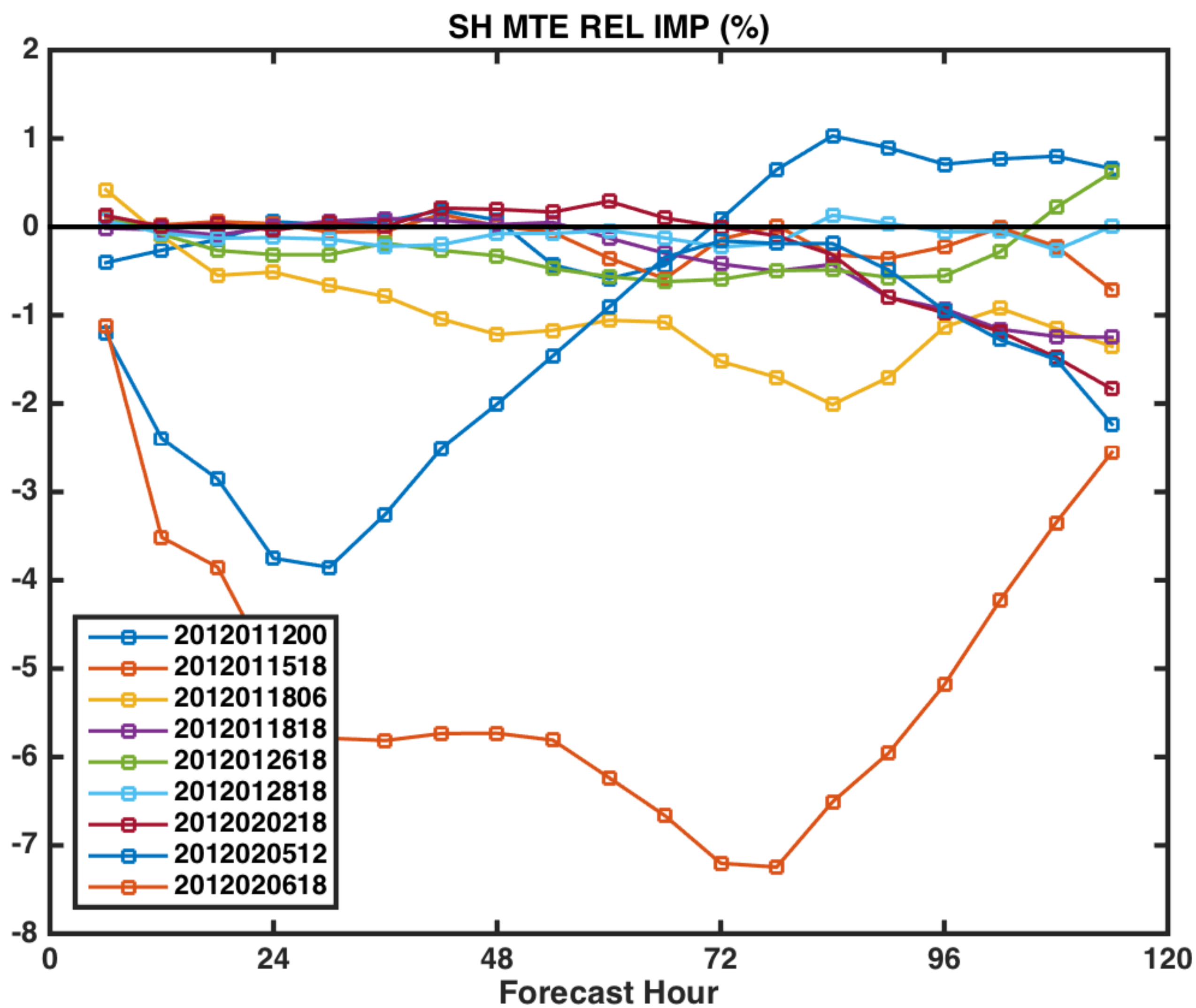


ALL CASES NH

Reduction of error is large, increase of error is small.

When PQC is done in the other hemisphere, the forecast skill changes little.

All 9 cases: impact in SH extratropics

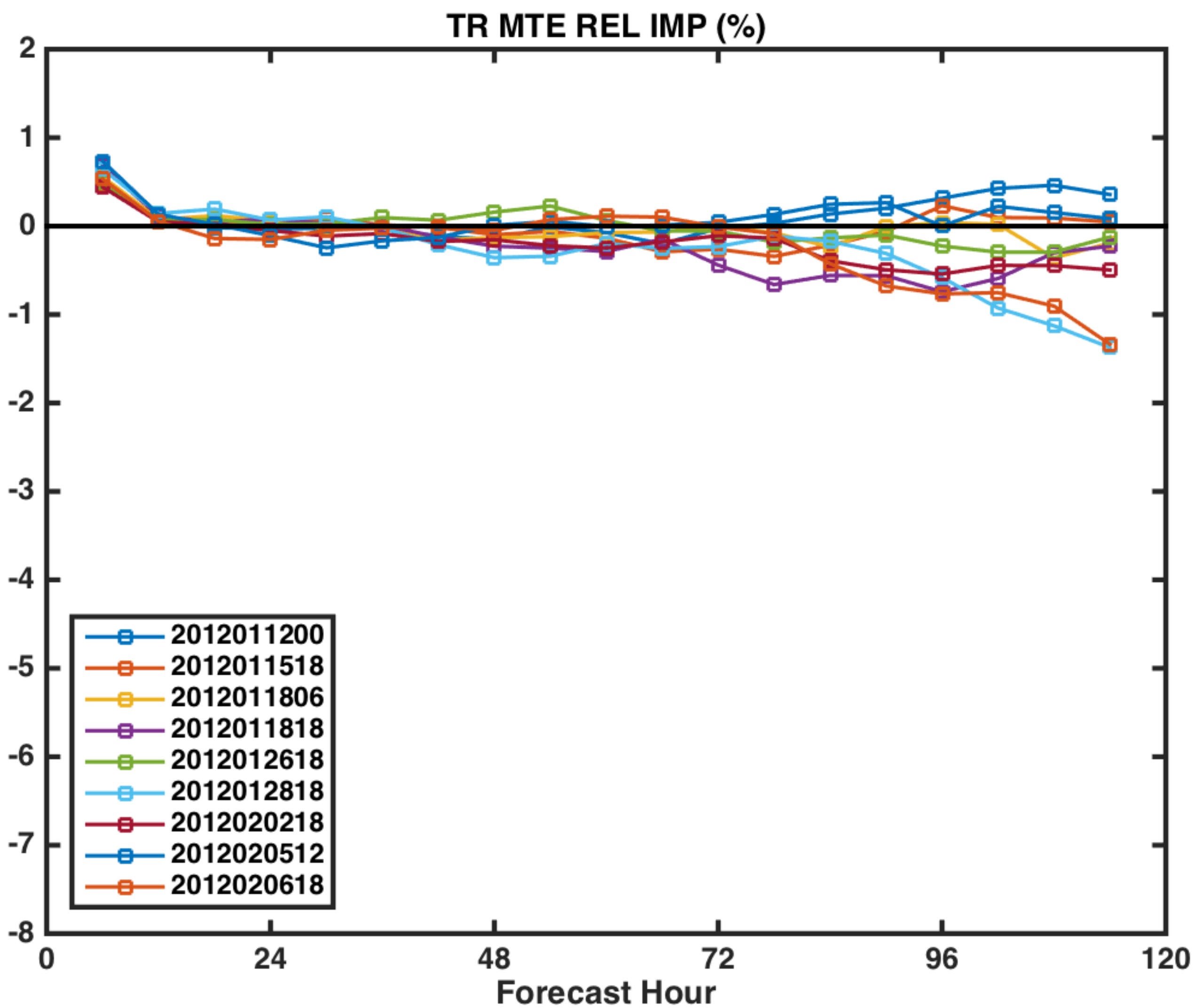


ALL CASES SH

Reduction of error is large, increase of error is small

When PQC is done in the other hemisphere, the forecast skill changes little.

All 9 cases: impact in Tropics



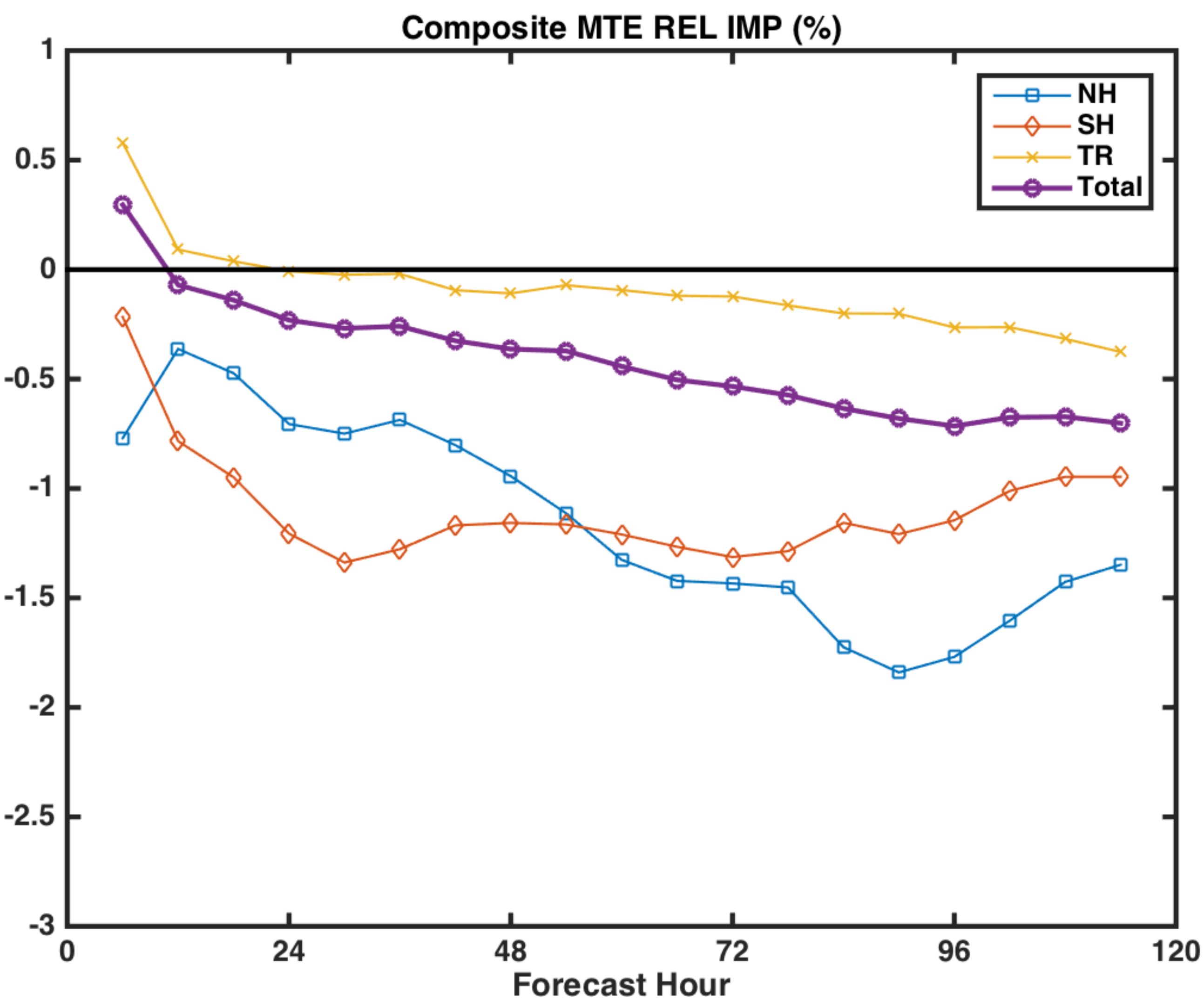
<u>ALL CASES TROPICS</u>

No flawed observations were withdrawn in the tropics.

The initial dropping of flawed obs in NH and SH extratropics introduces an initial noise in the tropics.

With time, the tropics improve due to NH and SH elimination of flawed obs.

All 9 cases: average % reduction of error



<u>AVERAGE OF ALL CASES</u>

The global % reduction of error improves with forecast length.

The dropping of flawed obs in NH and SH extratropics introduces an initial noise in the tropics.

With time, even the tropics improve due to NH and SH elimination of flawed obs.

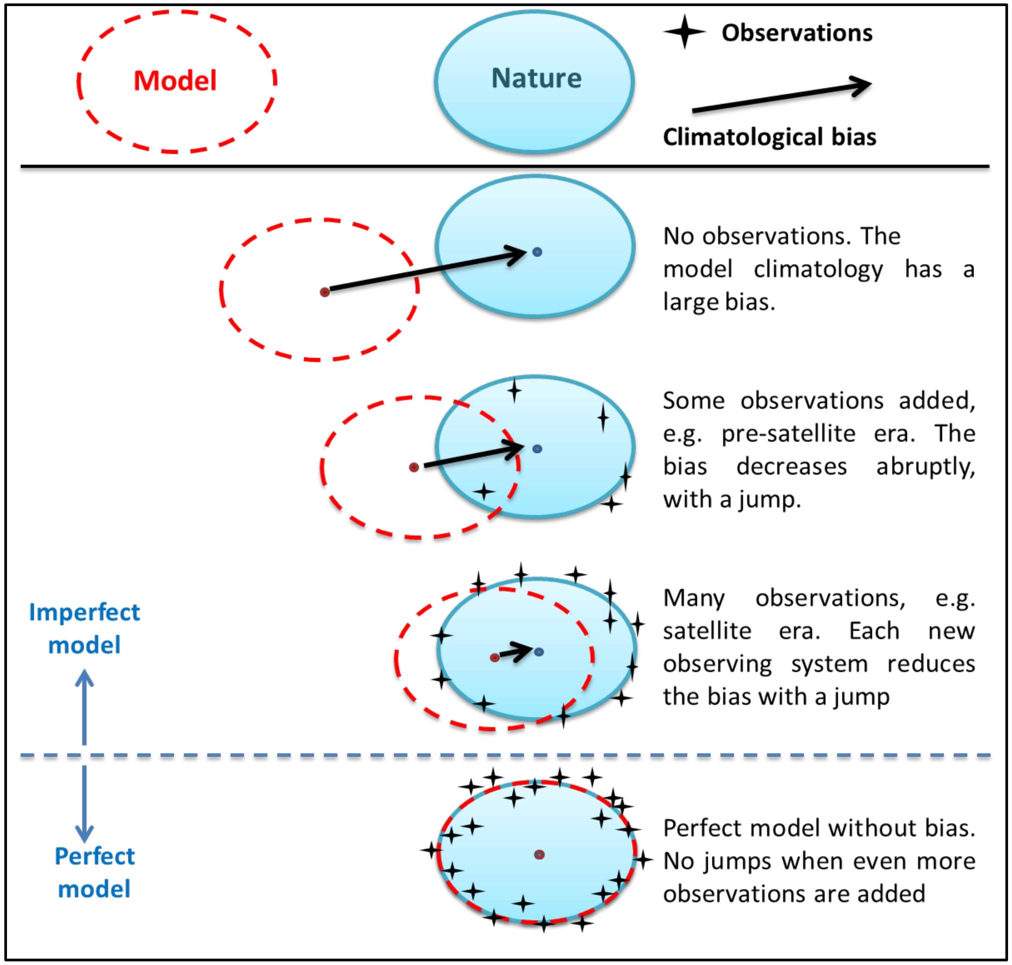
Implications for weather and climate prediction

- The results of PQC are very encouraging indeed!
- The improvements should accumulate on the GDAS when flawed observations are withdrawn online, not case by case.
- But we have to test this!
- A similar approach could be applied to the CFS!
- Our method relies in having many observations available to verify the short range (6 hour) forecast.
- A similar approach could be applied to short range (e.g., one month) ENSO forecasts: find the obs that make the one-month forecast worse and withdraw them.

Two weeks ago: Reanalysis Workshop

- The worst problem in reanalysis are the jumps that take place when new observing systems are used.
- They are due to the use of an imperfect model with model bias.
- Dr. Yan Zhou found the optimal solution to minimize reanalysis jumps using the bias correction of Danforth-Kalnay-Miyoshi (2007)

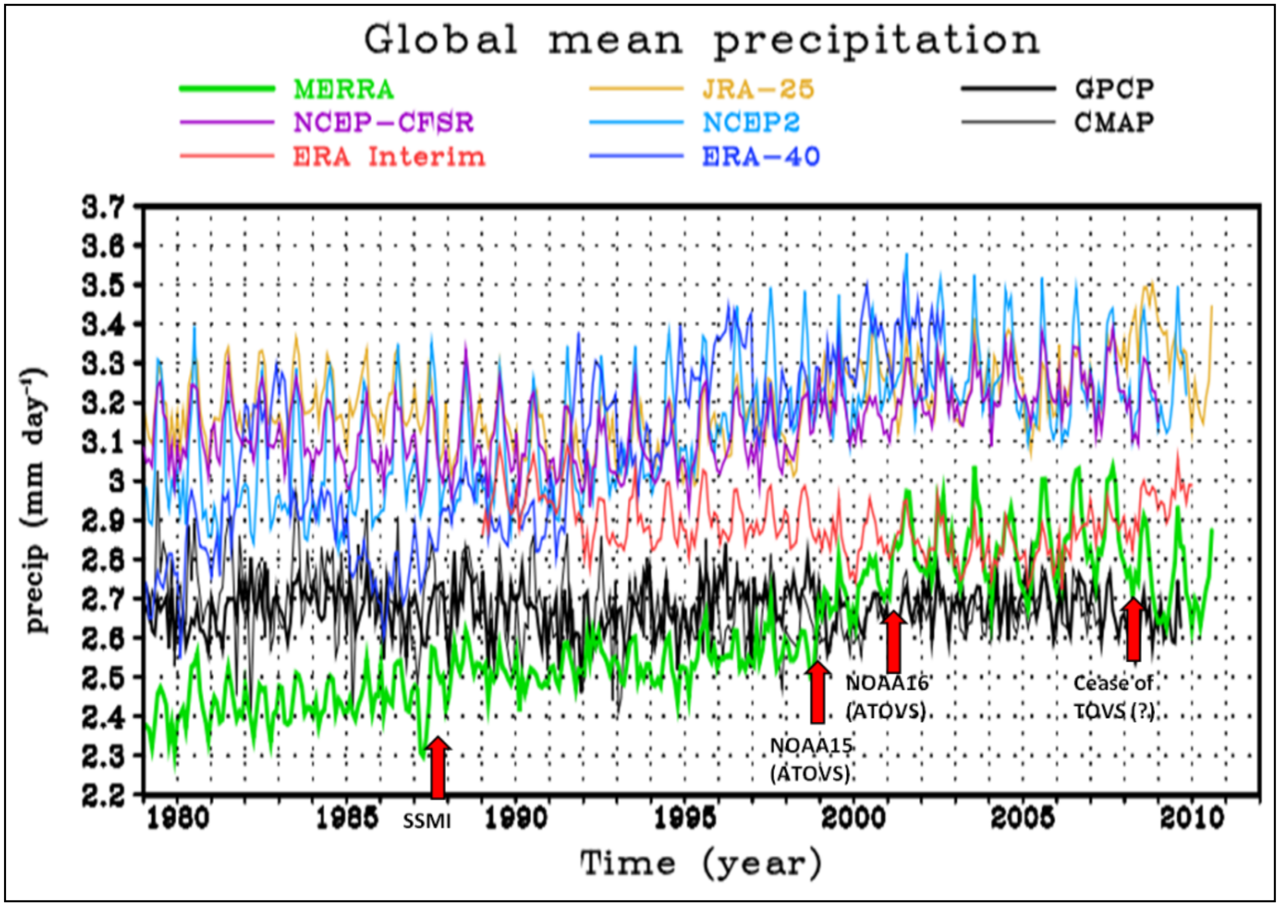
Why do we get reanalysis jumps? Model bias!



A schematic of "climate jumps" associated with observing system changes

- **The climatological bias between the forecast model and the nature decreases with a *jump* when a new observing system was assimilated.**
- **The purpose of Yan Zhou's dissertation is to find a solution to minimize the "climate jumps" associated with observing system changes.**

Example: MERRA global mean precipitation



Global monthly mean precipitation (mm/day) time series for MERRA (green), several other reanalyses, and GPCP and CMAP (black) (Chen et al., 2012)

- **Jumps in the MERRA global mean precipitation time series appeared simultaneously with introducing or ceasing different types of satellite observations, like SSM/I and ATOVS (red arrows)**

How can we estimate and correct model bias?

- The best current estimate of nature is the analysis
- The First Guess (6hr forecast) contains the initial forecast errors (before they grow nonlinearly)
- Analysis - First Guess = Analysis Increments (**AI**) = - Initial (linear) model errors
- **Time average of AI is the best estimate of the error growth due to model bias in 6 hr**
- Danforth, Kalnay and Miyoshi (DKM-2007) estimated the 6hr errors of the SPEEDY model.
- Estimated the average SPEEDY model error (bias) by averaging over several years the 6 hour forecast (started from reanalysis R1) minus the reanalysis.

DKM-2007 results

- Estimated the monthly mean 6hr forecast bias
- Corrected the model by adding (–bias/6hr) to each variable time derivative, at each grid point.

Results

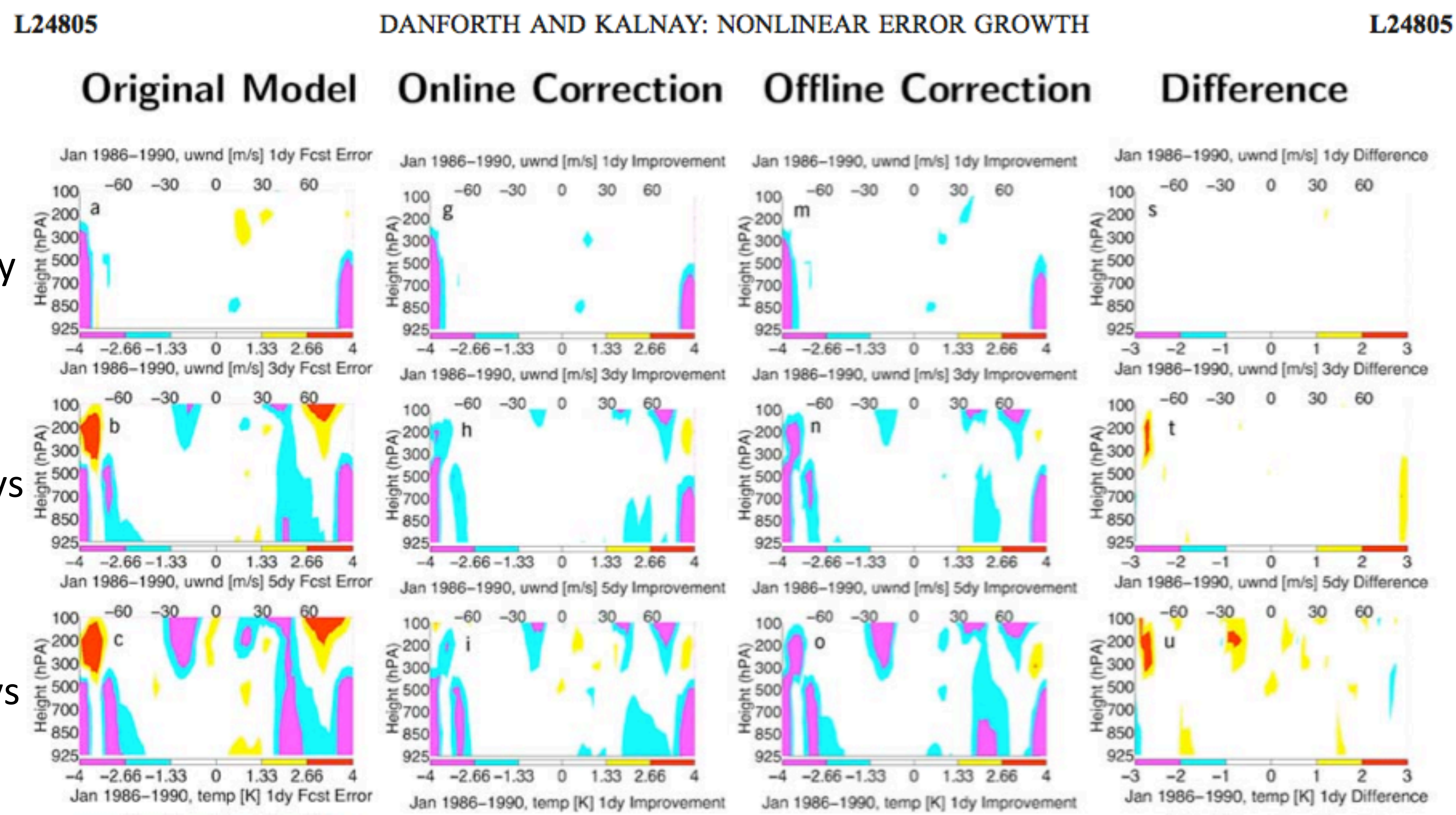
- The bias correction after 3 or 5 days was <u>the same</u> as the best *a posteriori bias* correction.
- But the random errors were **smaller**.
- The dominant EOFs of the 6hr debiased forecast errors were the errors in the diurnal cycle.
- It was possible to estimate the systematic errors for anomalies (e.g., ENSO, lows over land or over ocean)

The model corrected online did at least as well as the model statistically corrected off-line

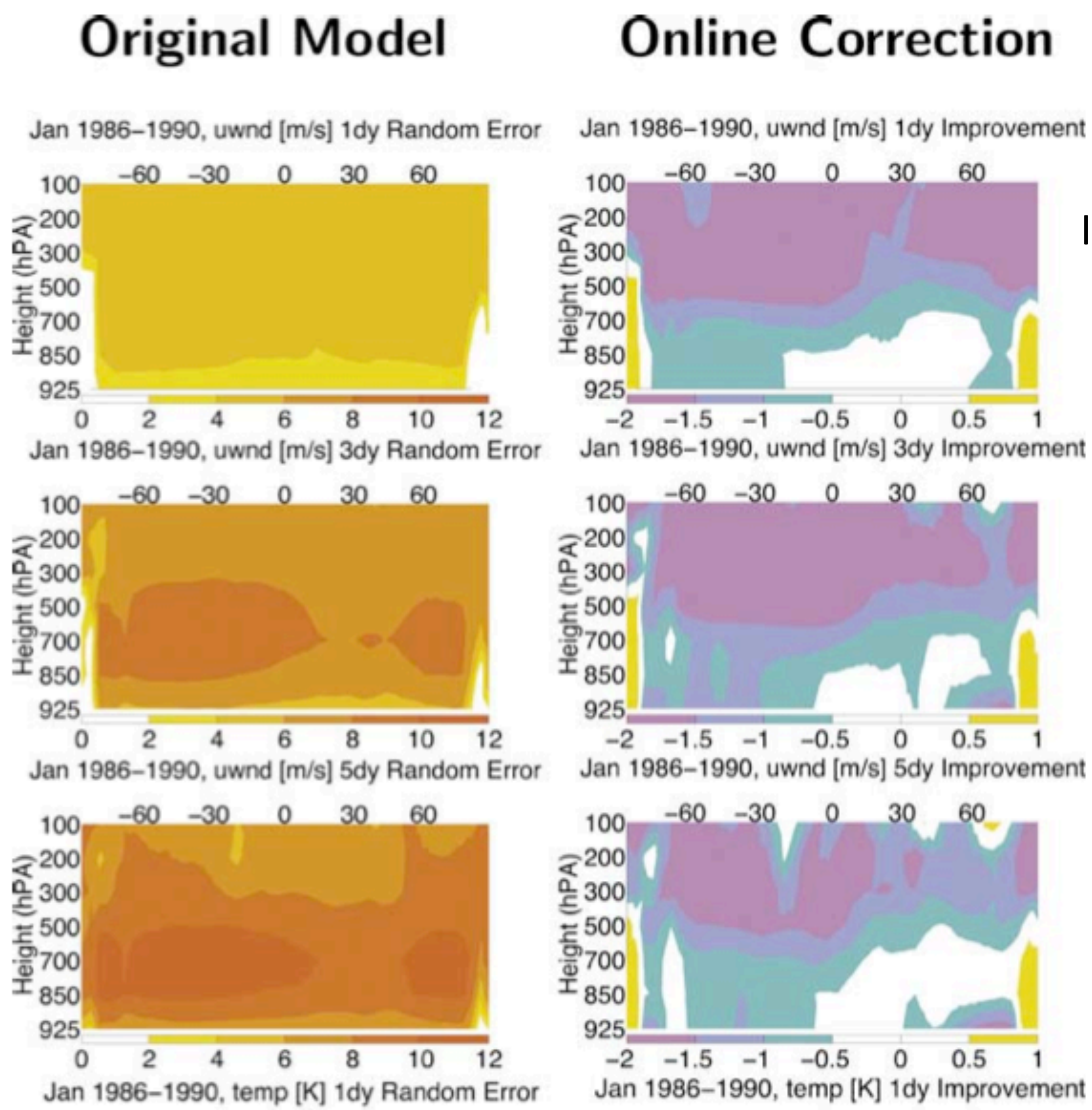
1 day

3 days

5 days



And the random errors were significantly smaller!



1 day

3 days

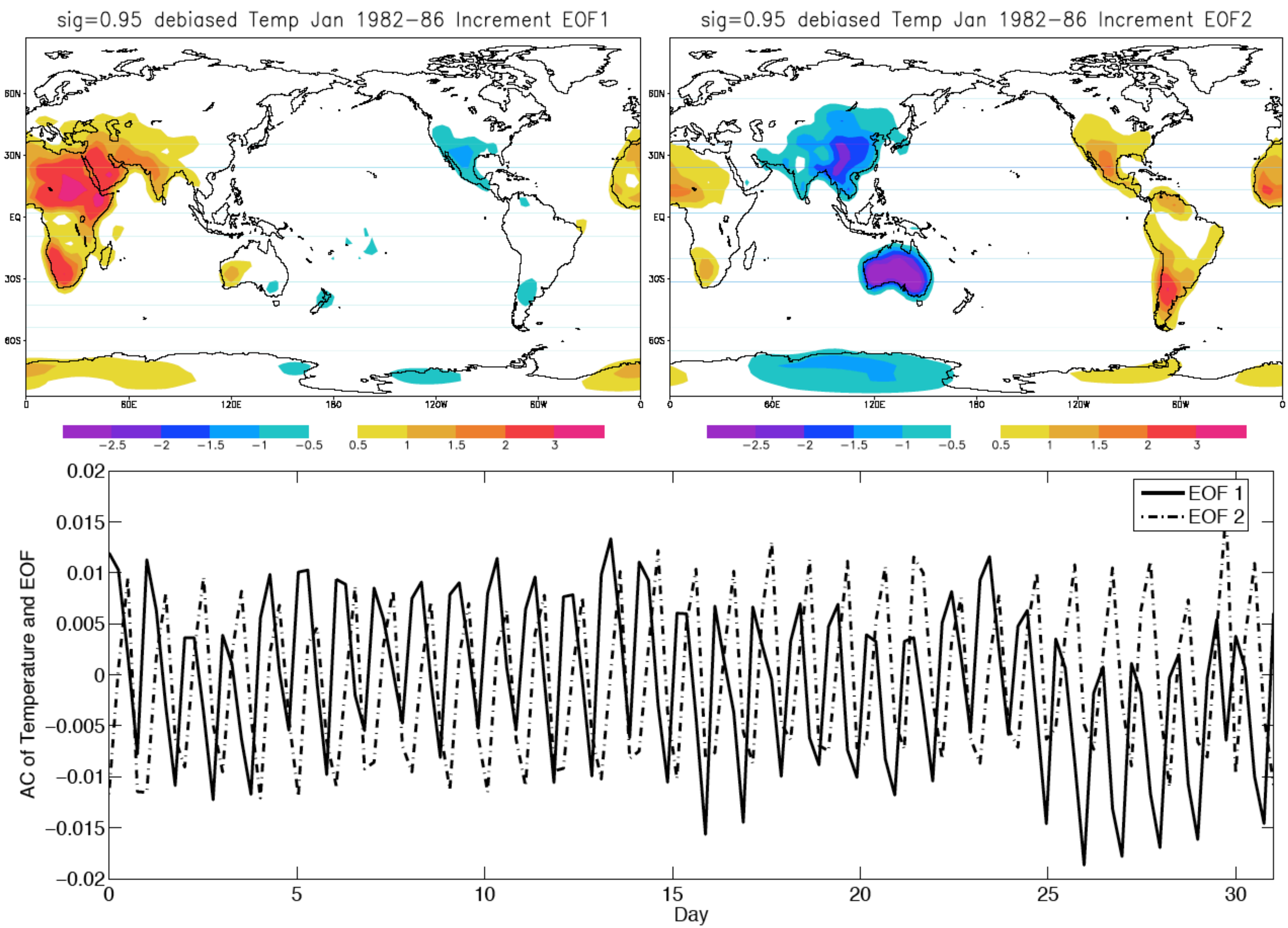
5 days

Improvements

How to find the diurnal cycle model errors using EOFs from a Reanalysis (Danforth et al., 2007)

Estimated the average SPEEDY model error (bias) by averaging over several years the 6 hour forecast (started from reanalysis) minus the reanalysis.

Then they computed the EOFs of the anomaly in the model error, and found two dominant EOFs representing the model error in representing the diurnal cycle:



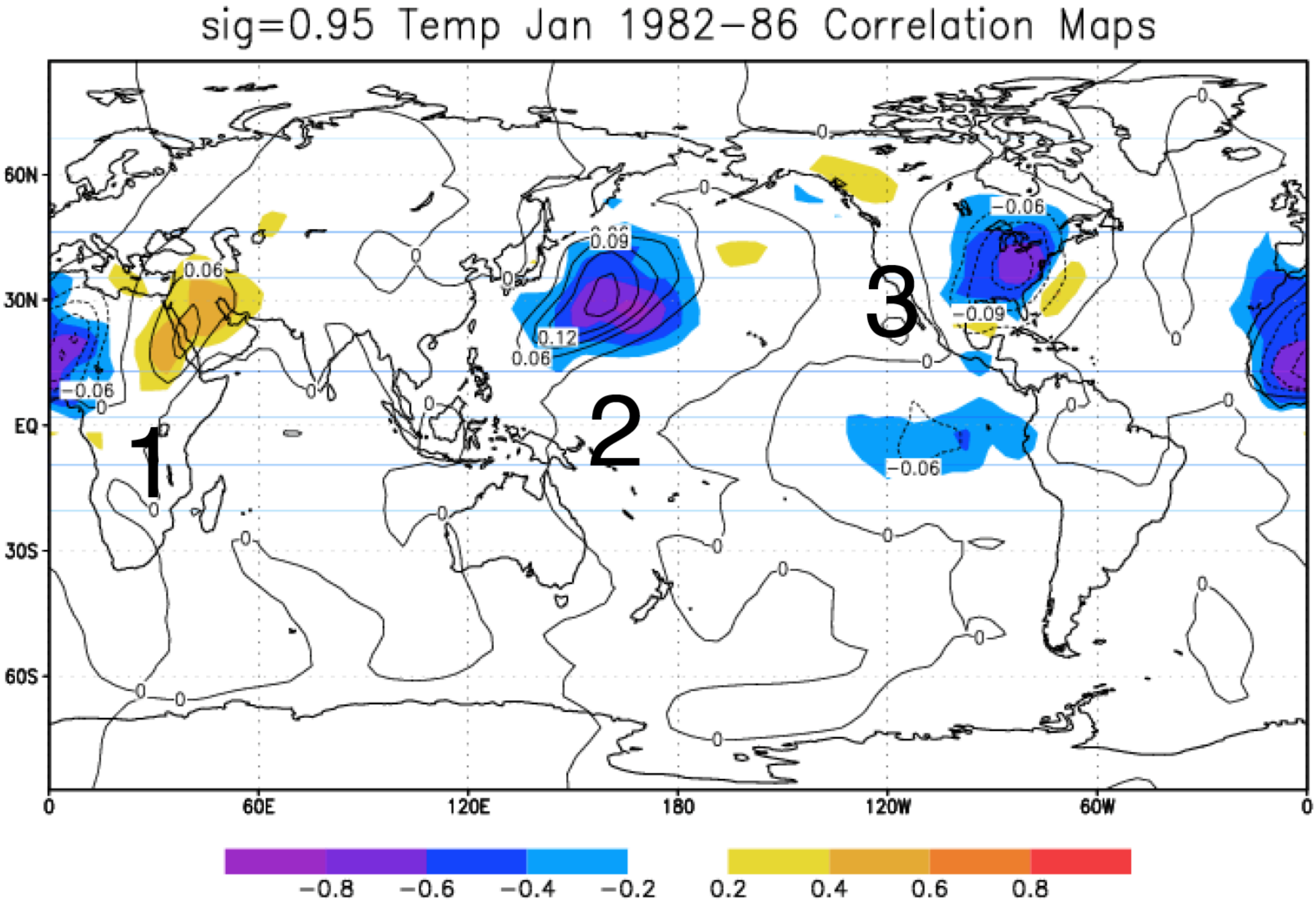
sig=0.95 debiased Temp Jan 1982–86 Increment EOF1
sig=0.95 debiased Temp Jan 1982–86 Increment EOF2
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
0
−2.5 −2 −1.5 −1 −0.5
0.5 1 1.5 2 3
EOF 1
EOF 2
AC of Temperature and EOF
0.02
0.015
0.01
0.005
0
−0.005
−0.01
−0.015
−0.02
0 5 10 15 20 25 30
Day

How to find the state dependent errors using coupled SVD's (Danforth et al., 2007)

Three leading coupled SVD's of the covariance of 6 hr forecast errors and corresponding model state anomaly for T at sigma=0.95. Contours: state anomaly, colors: heterogeneous correlation with forecast errors.

Over land, the corrections suggest the anomalous temperatures are too strong, and over ocean too weak and too far to the west.

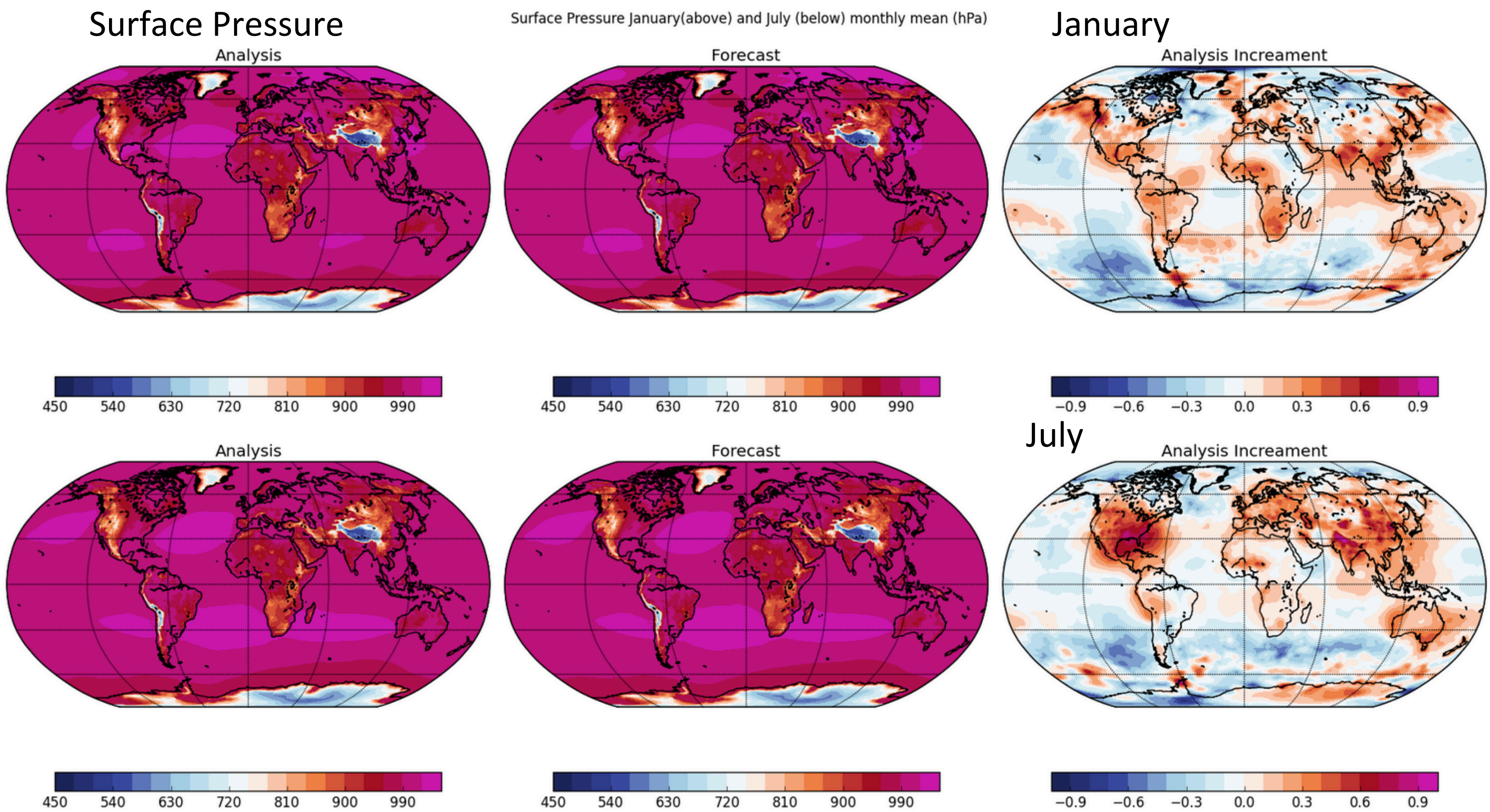
This can be extended to improving forecasts using coupled SVD's


sig=0.95 Temp Jan 1982-86 Correlation Maps
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
0
1
2
3
0.06
-0.06
0.09
0.12
-0.09
-0.8
-0.6
-0.4
-0.2
0.2
0.4
0.6
0.8

Implications for improving the model bias

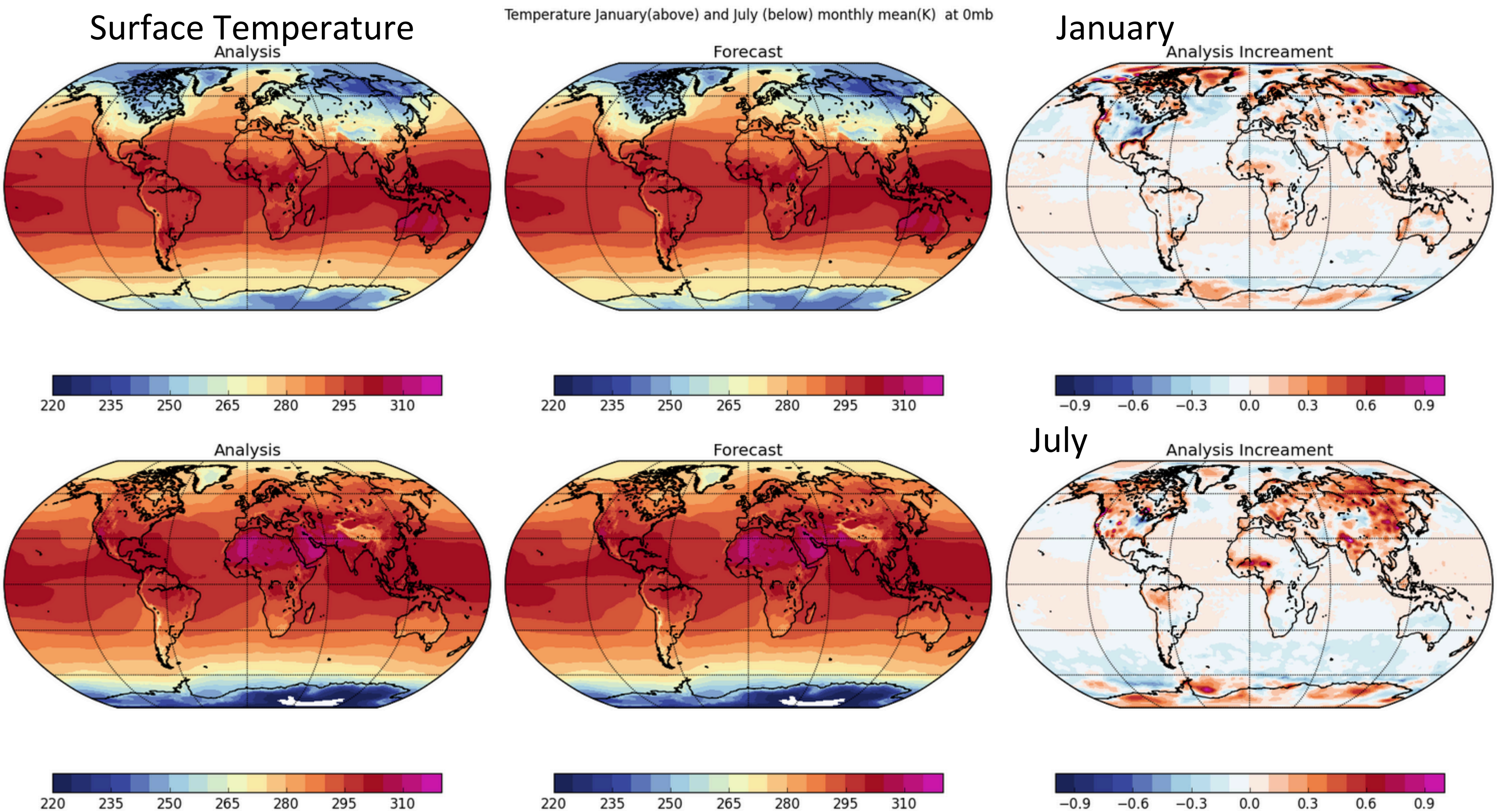
- The DKM2007 method gave very good results with the SPEEDY model, using R1 as an approximation of the true atmosphere.
- The bias/6hr was added to the SPEEDY time derivatives (u,v,T,p_s).
- This corrected the bias, getting similar or better results than an *a posteriori* bias correction! In addition, random forecast errors were also reduced.
- It was also used to improve the diurnal cycle and to find the state dependent systematic errors (e.g., during an El Niño).
- **It can be tried on the GFS (or the CFS!) taking advantage of the Analysis Increments, i.e., the difference between the Analysis and the Forecast.**
- Dr. Fanglin Yang very kindly provided us (Kriti B., Jim Carton and me) with 2014 and 2013 Analyses and forecasts. Kriti got these results yesterday! ☺

First results: 2014 Analyses, Forecasts and AIs



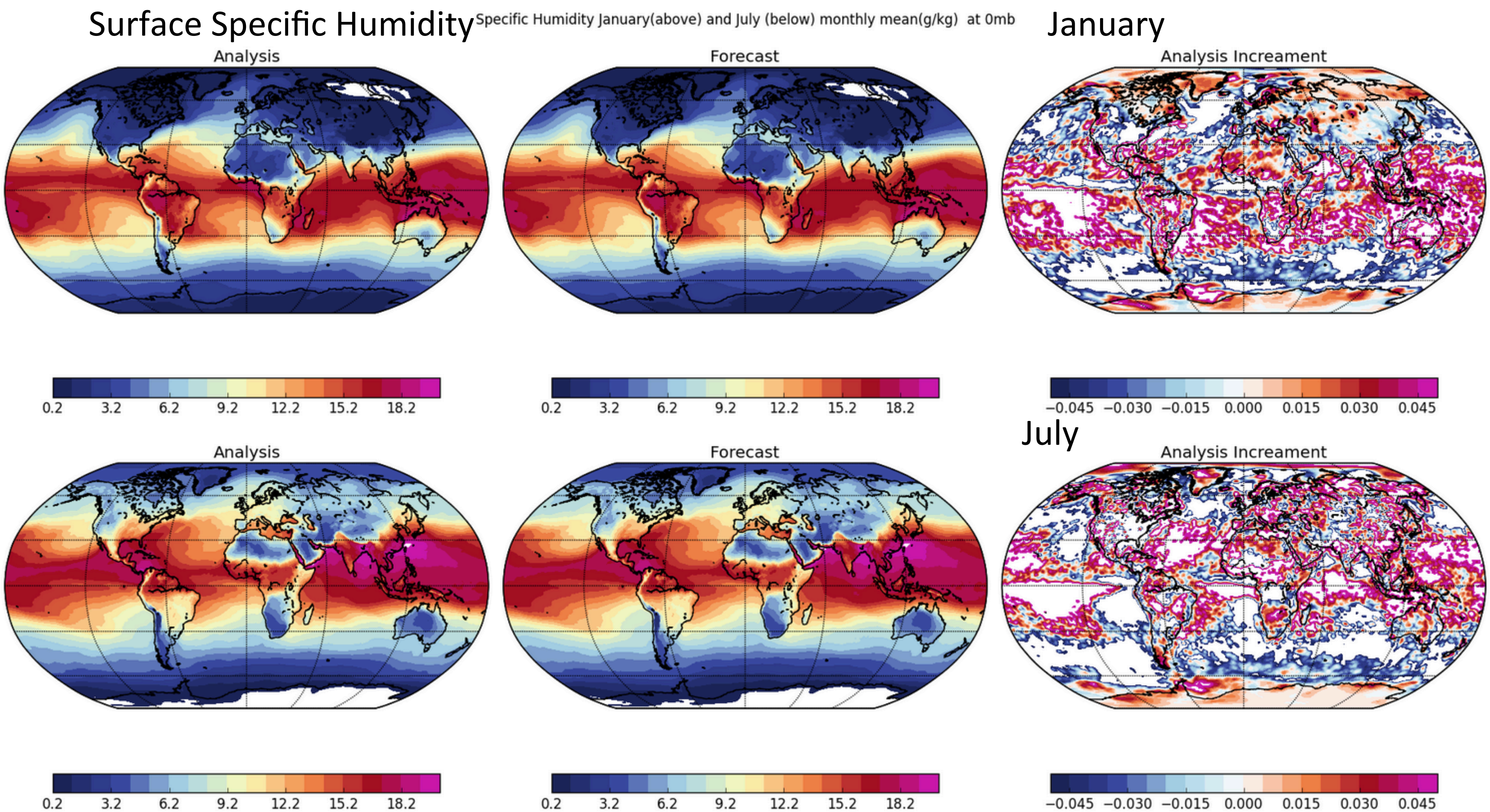
P_s is too low over continents, too high over oceans in both winter and summer.

First results: 2014 Analyses, Forecasts and AIs



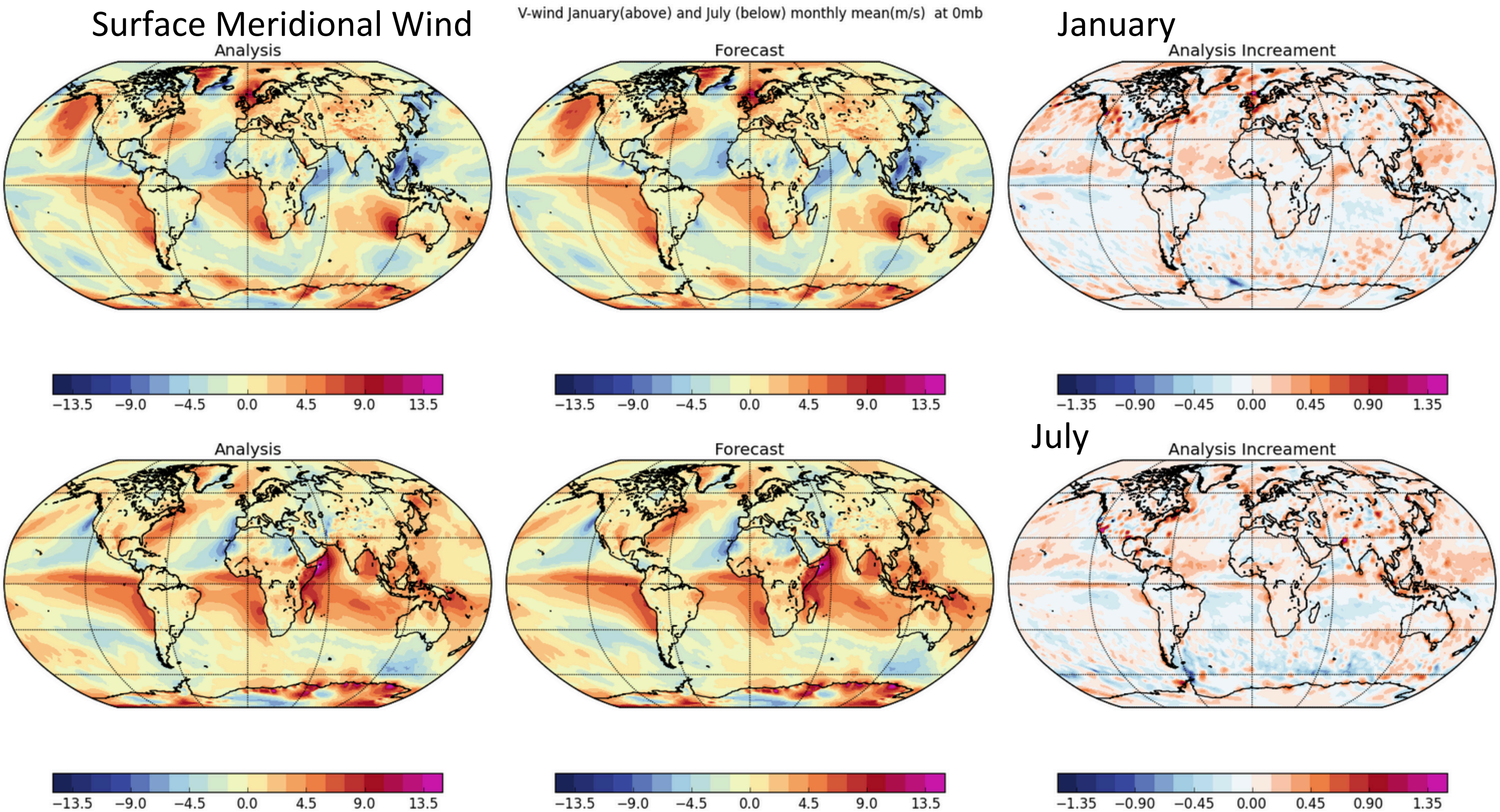
T_s is too low over continents in the summer, too high in the winter.

First results: 2014 Analyses, Forecasts and AIs



Q_s is a noisy mess!

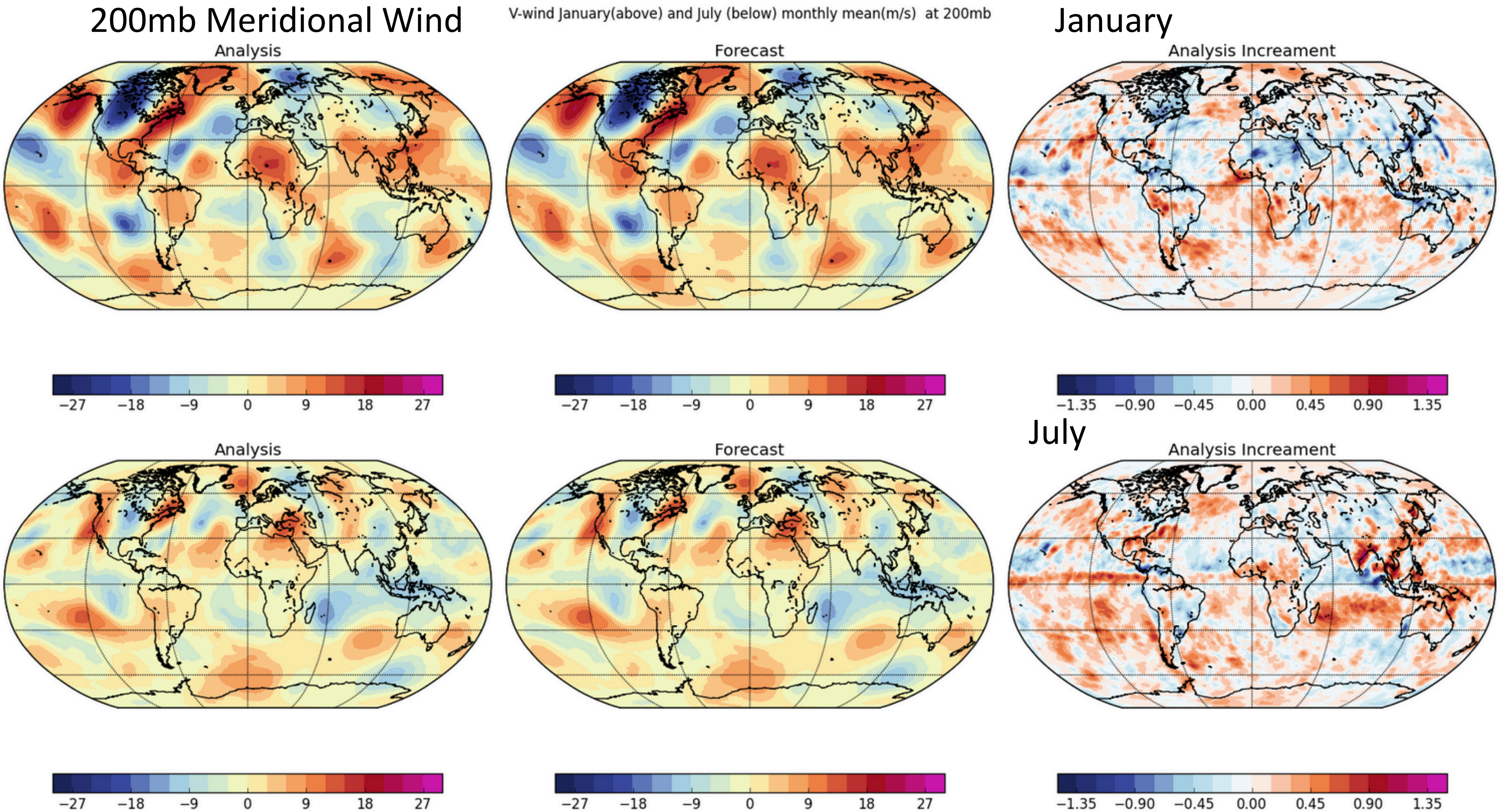
First results: 2014 Analyses, Forecasts and AIs



At the Equator there are bands of excessive divergence and convergence North and South of the Equator

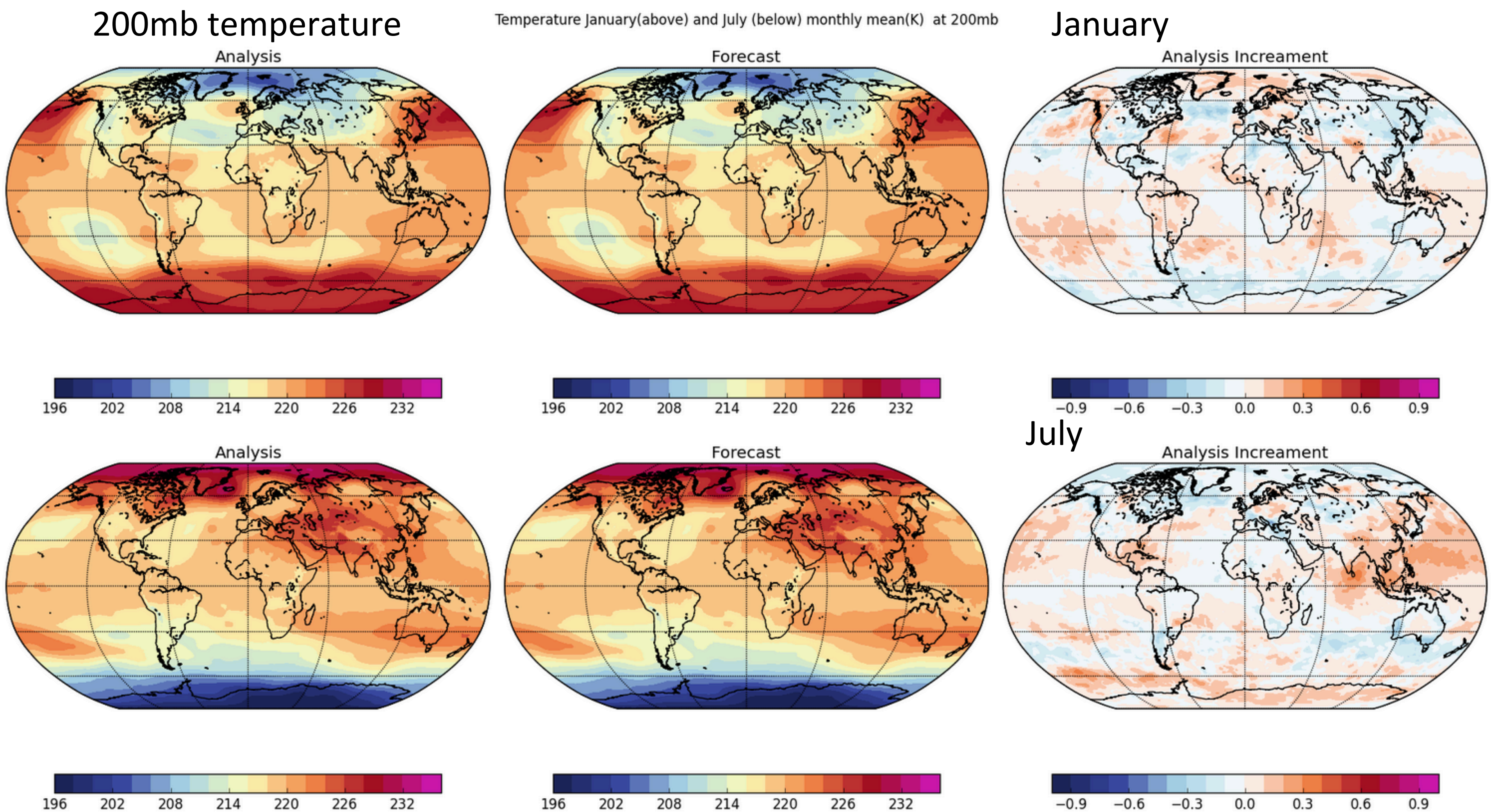
First results: 2014 Analyses, Forecasts and AIs

200mb Meridional Wind



At 200mb the bands of divergence seem too weak.

First results: 2014 Analyses, Forecasts and AIs



200mb: Poles are too cold in winter, too warm in summer.
Mid-lat continents are too warm in winter.

How should we proceed to reduce model bias?

- Check the robustness of the monthly average AI (2014 vs. 2013, July vs. August), earlier years.
- Do they change significantly with model resolution?, model physics?
- Try doing seasonal filtering with 2-3 Fourier components, as Yan Zhou did.
- Find why moisture increments are so noisy. Maybe discard them?
- Perform exploratory low resolution (T254) experiments correcting the perceived model biases by adding AI/6hr to each variable (except for Q?)
- Explore the diurnal cycle of the AI (error correction). Test if the diurnal cycle errors can be reduced.
- …

Improving non-Gaussian Observations

Effective assimilation of Precipitation

Guo-Yuan Lien, E. Kalnay and T. Miyoshi (Tellus 2013), Lien (2014), Lien et al. (2015a, 2015b)

- Assimilation of precipitation has generally failed to improve forecasts beyond a day.
- A new approach deals with non-Gaussianity, and assimilation of both zero and non-zero precipitation.
- Rather than changing moisture to force the model to rain as observed, the LETKF changes the **potential vorticity**.
- **The model now "remembers" the assimilation, so that medium range forecasts are improved.**

How to transform precipitation *y* to a Gaussian y_{transf}

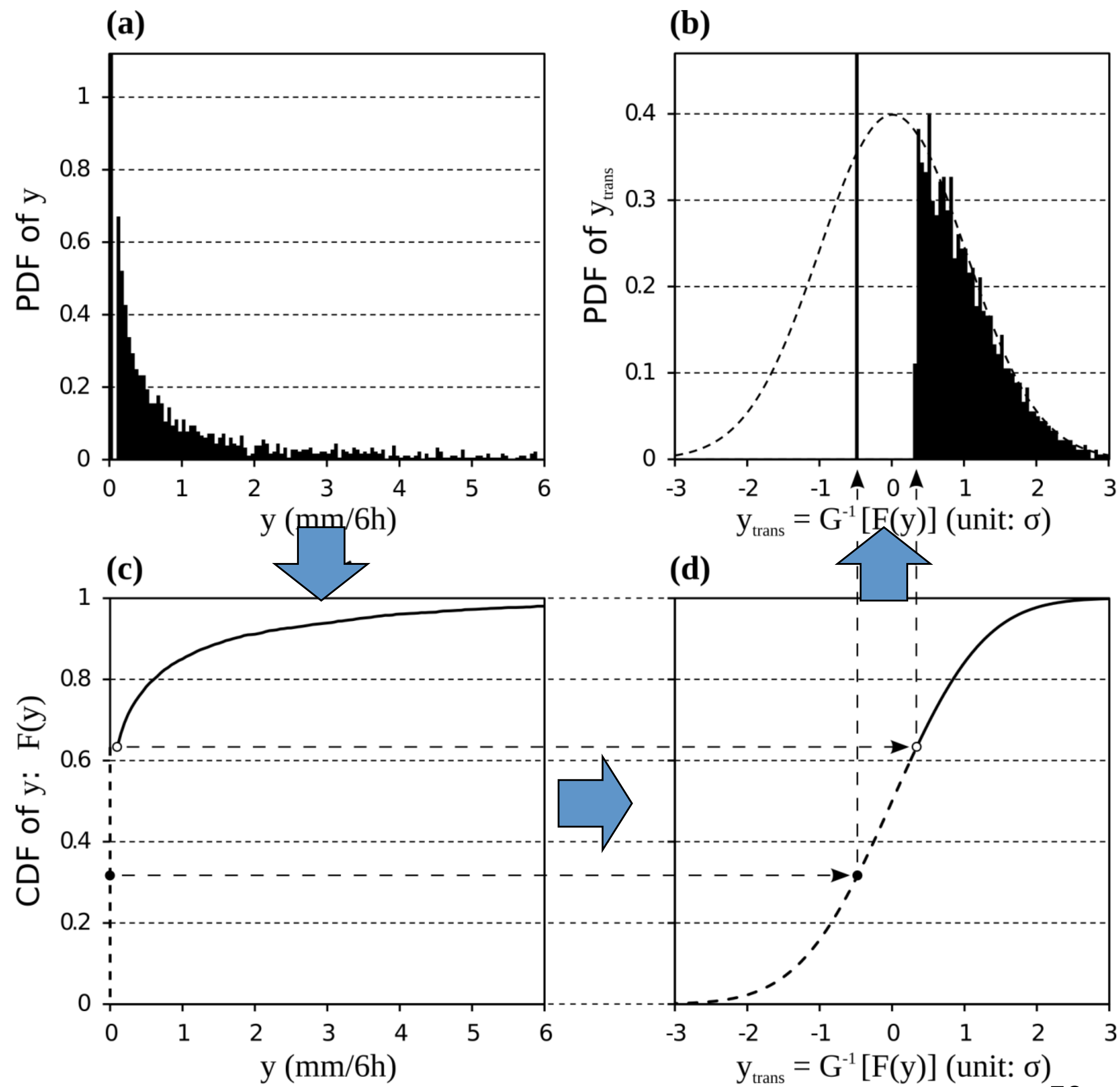
Start with pdf of *y*=rain at every grid point.

"No rain" is like a delta function that we cannot transform.

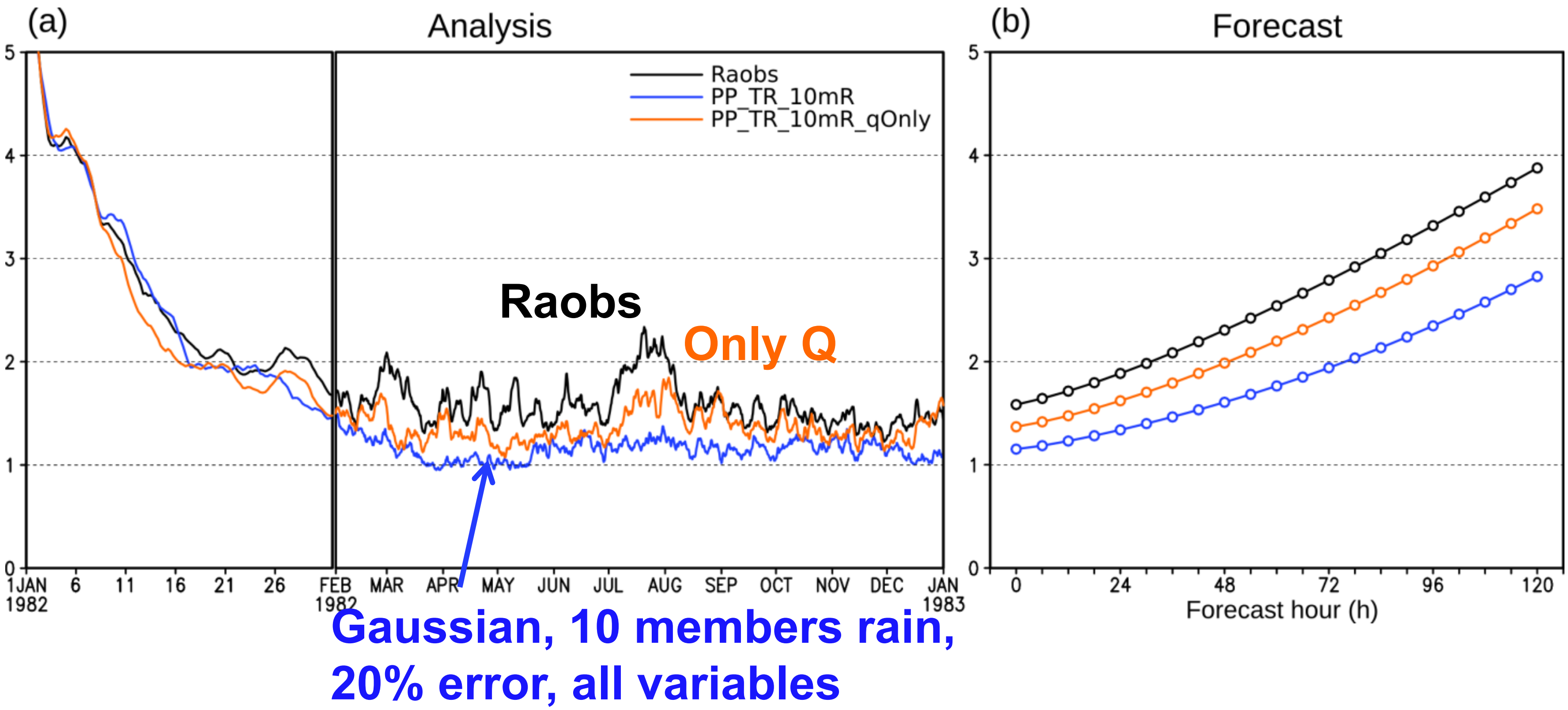
We assign all "no rain" to the median of the no rain CDF.

We found this works as well as more complicated procedures.

It allows to assimilate both rain and no rain.



$$G^{-1}(x) = \sqrt{2}\,erf^{-1}(2x-1)$$

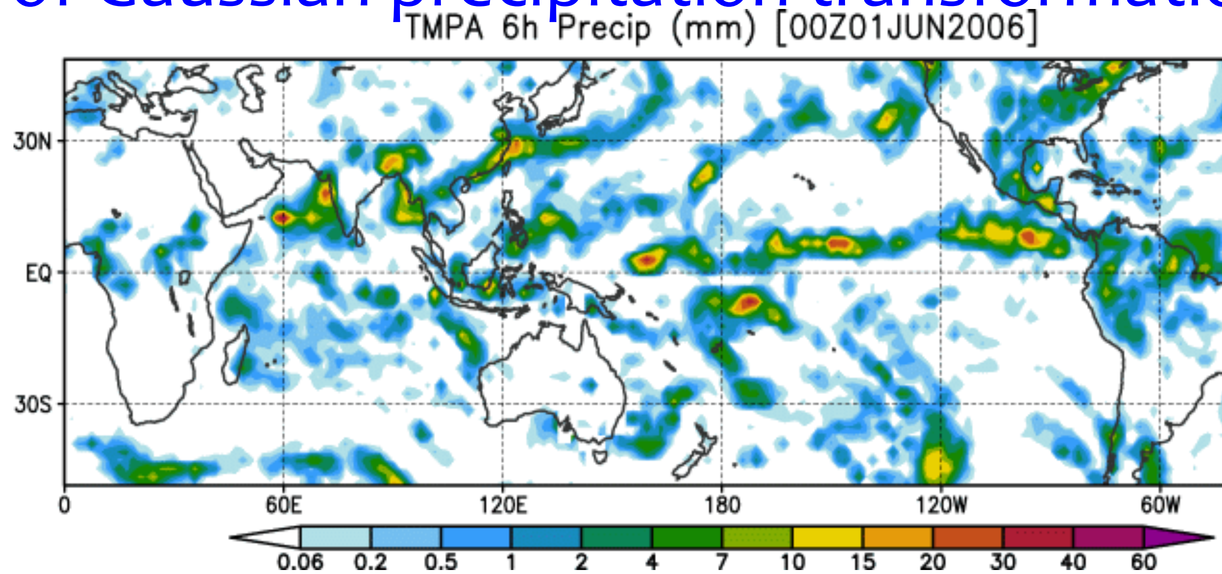


- Main result: with at least 10 ensemble members raining in order to assimilate an obs, updating all variables (including vorticity), with Gaussian transform, and rather accurate observations (20% errors), the analyses and forecasts are much improved!
- Updating only Q is much less effective.
- The 5-day forecasts maintain the advantage!

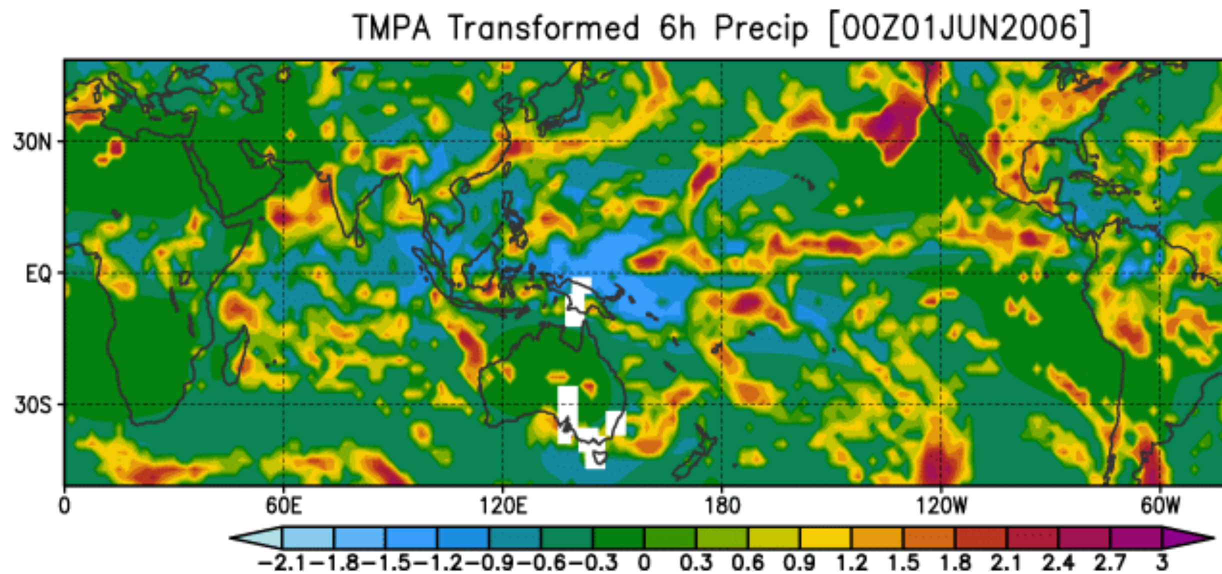
REAL OBSERVATIONS (TMPA)

Example of Gaussian precipitation transformation

Original variable



Transformed variable

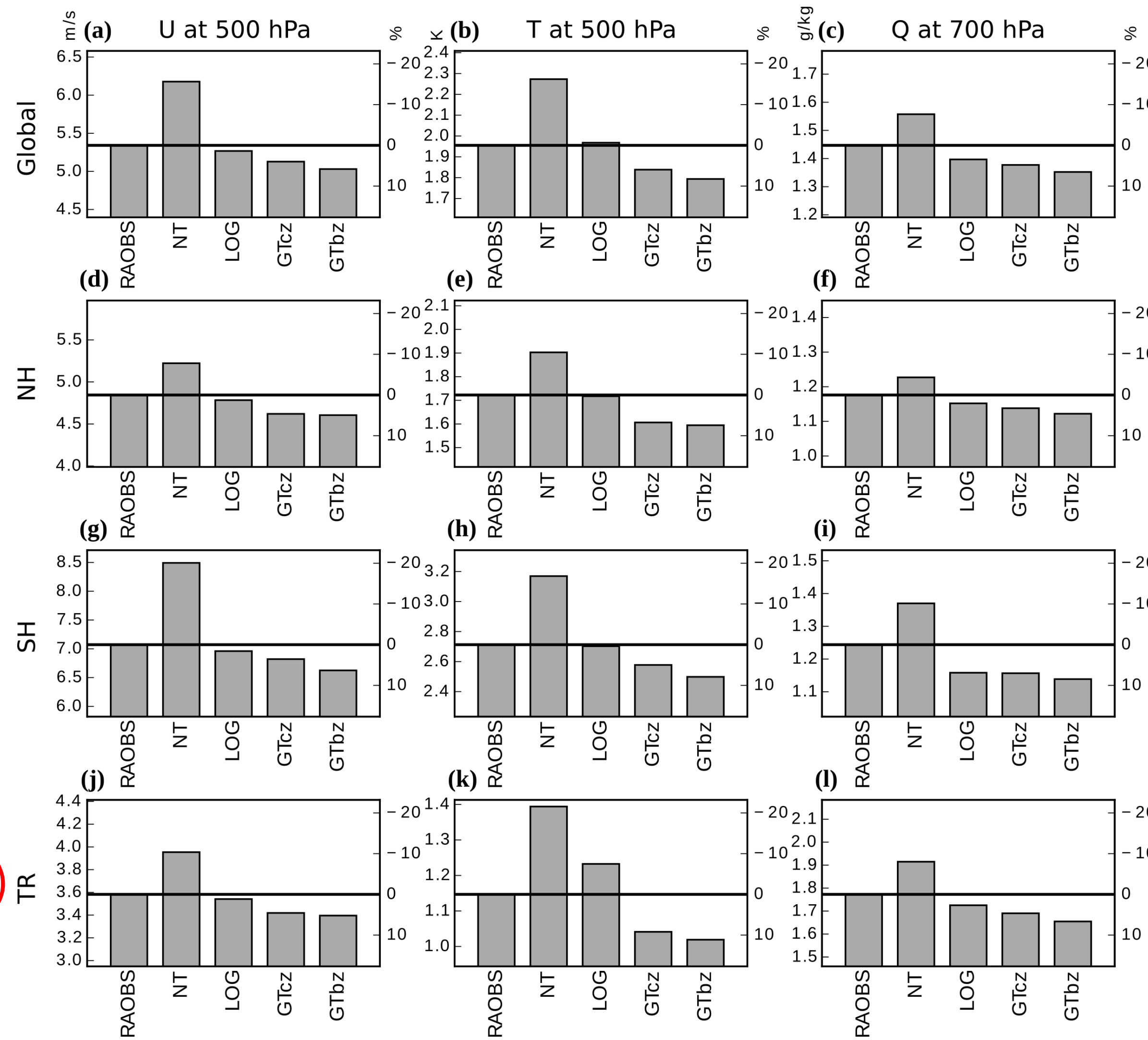


Assimilating TRMM rain with a GFS T62 model verified against ERA Interim (RMSE)

24hr forecast RMSE

Comparing RMSE of

Control (RAOBS) (no assim of pp)
Assim. with No Transform
Assim. with LOG Transform
Assim. w Gaussian Transform cz
Assim. w Gaussian Transform bz

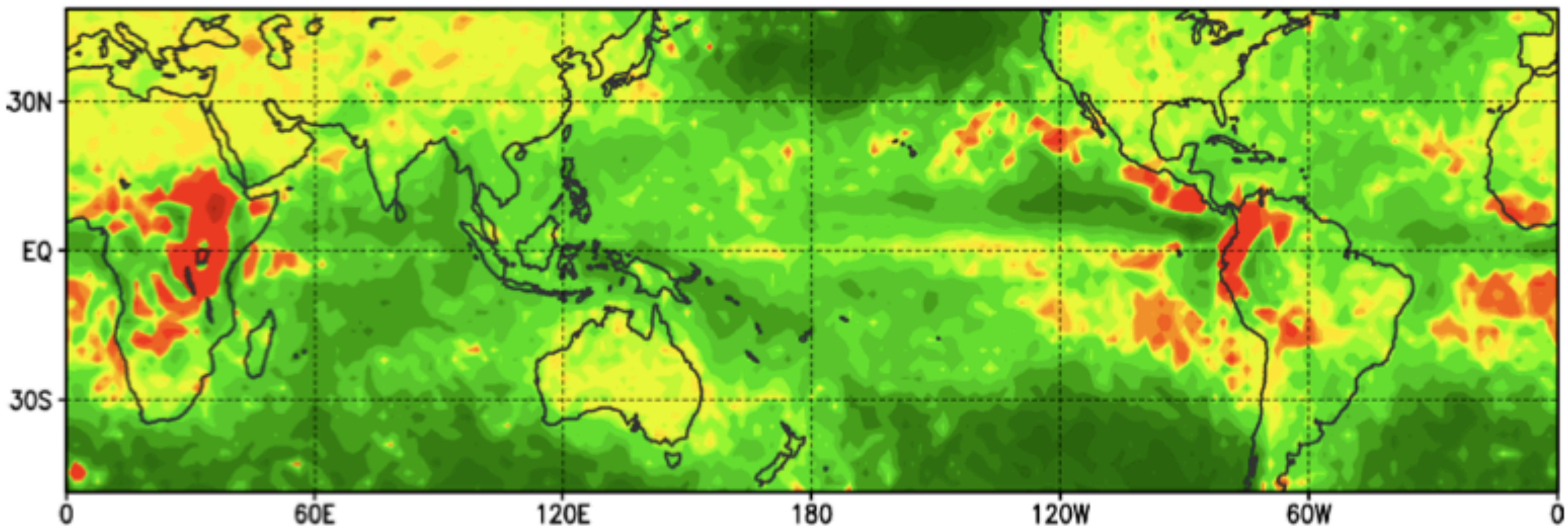


Results
No Transform is the worst
LOG Transform~RAOB (no pp assim)
GT are the best

Guo-Yuan Lien (2014): Efficient assimilation of precipitation

EFSO average impact of **rain obs.**

(a) Average obs impact (10^{-4} J/kg) [MTE, EFT=6h]: All obs

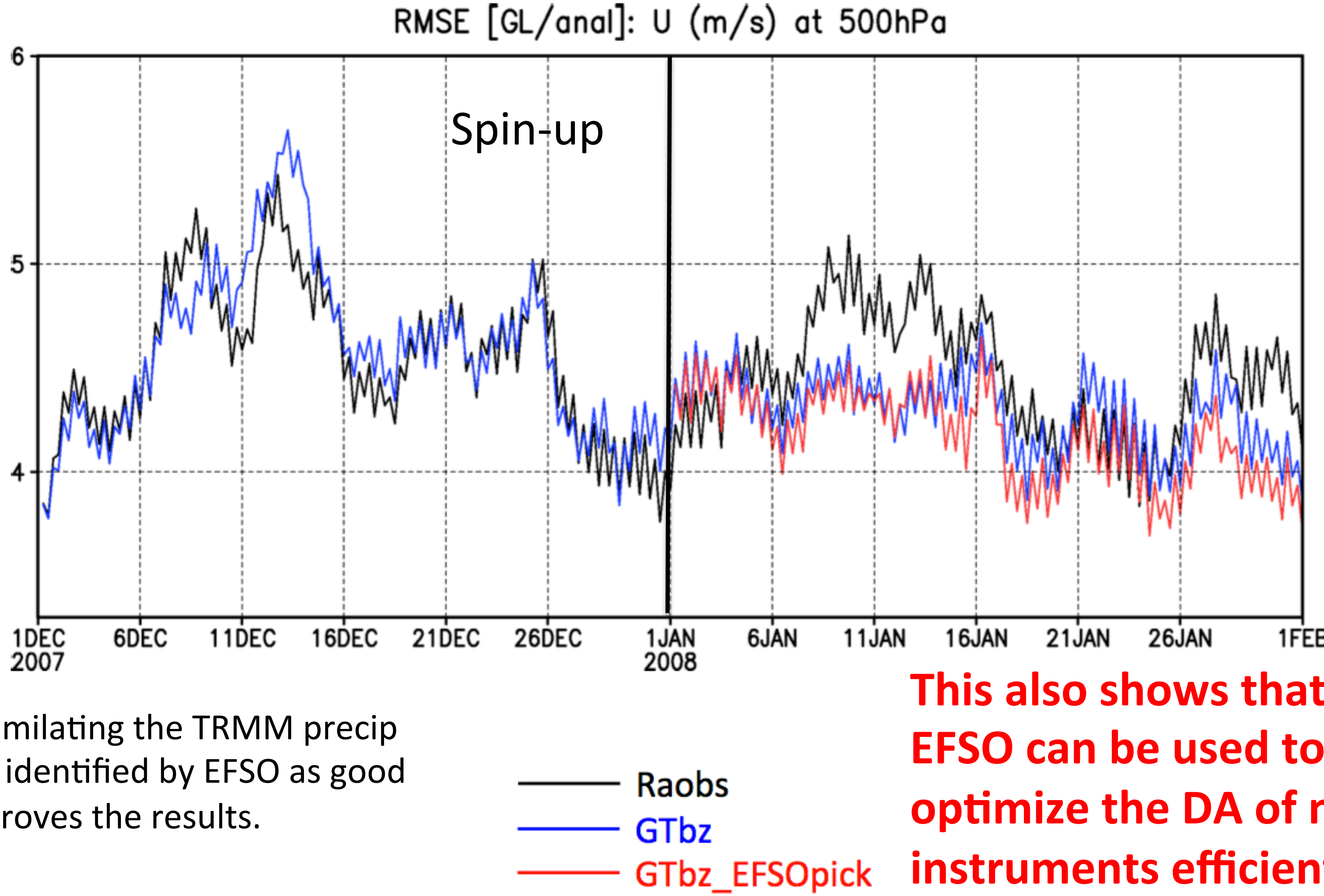


Assimilating only the precip obs identified by EFSO as good improved the results!

This also shows that EFSO can be used to optimize the DA of new instruments efficiently!

One-month time series: Analysis U (m/s) at 500 hPa

Guo-Yuan Lien (2014)



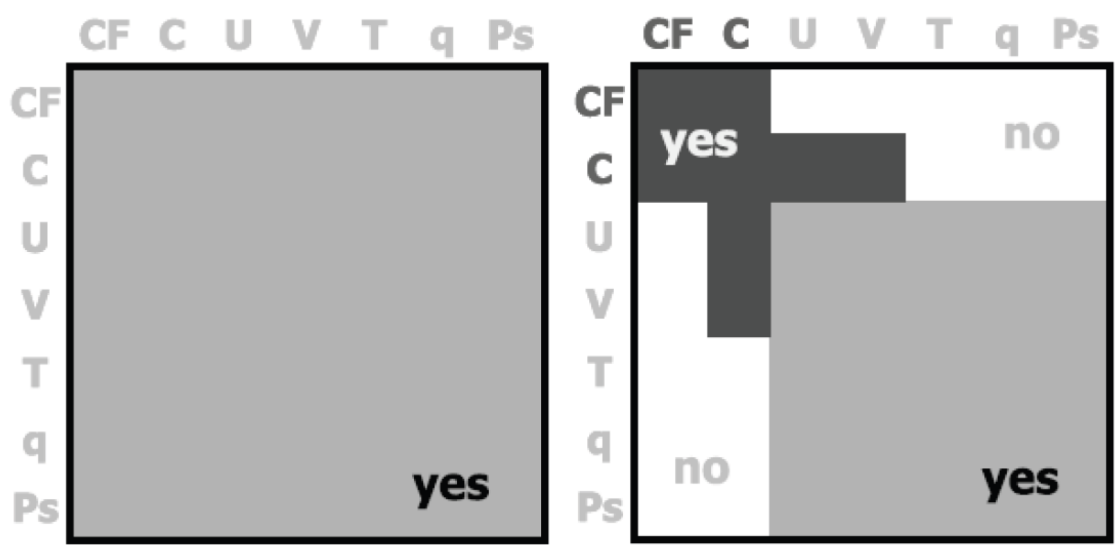
Assimilating the TRMM precip obs identified by EFSO as good improves the results.

This also shows that EFSO can be used to optimize the DA of new instruments efficiently!

Improve the models: Parameter estimation and estimation of bias using DA

- Model tuning on long time scales should be done with EnKF parameter estimation.
- Kang et al., JGR, 2011, 2012 showed that evolving surface carbon fluxes can be estimated accurately at the model grid resolution from simulated atmospheric CO2 observations (OCO-2) as evolving parameters.
- Another approach is the use of analysis increments to estimate model bias (Greybush et al., 2012, Mars) and even state-dependent model bias (e.g., El Niño bias), as in Danforth et al. 2007.

Surface carbon fluxes CF from atmospheric assimilation of meteorological variables and CO2 obtained as evolving parameters (OSSE). Kang et al., JGR, 2011, 2012



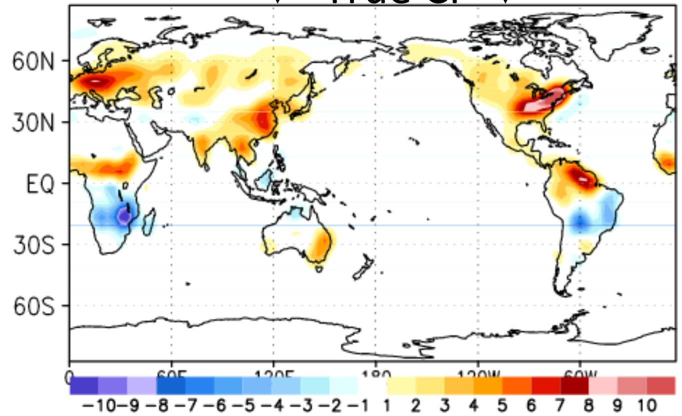
"Variable Localization"

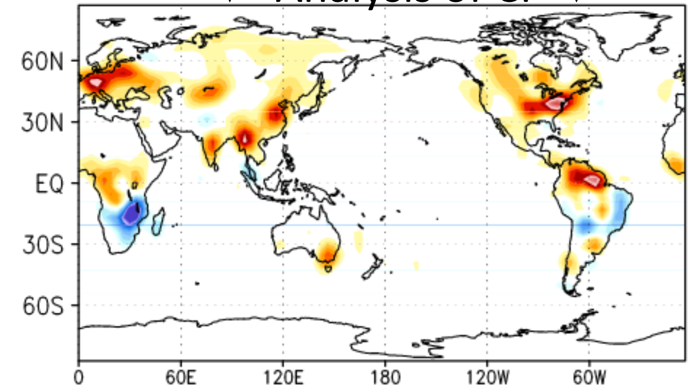
OSSE Results

▼ True CF ▼

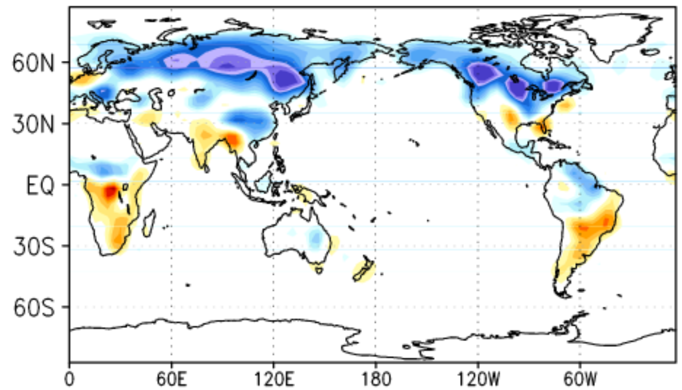
▼ Analysis of CF ▼

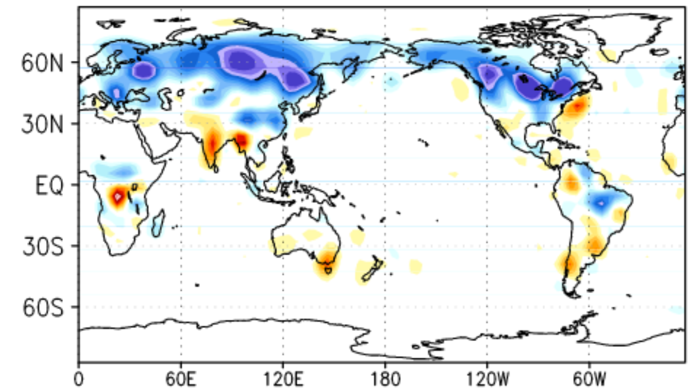
00Z01APR ▶
After three months of DA





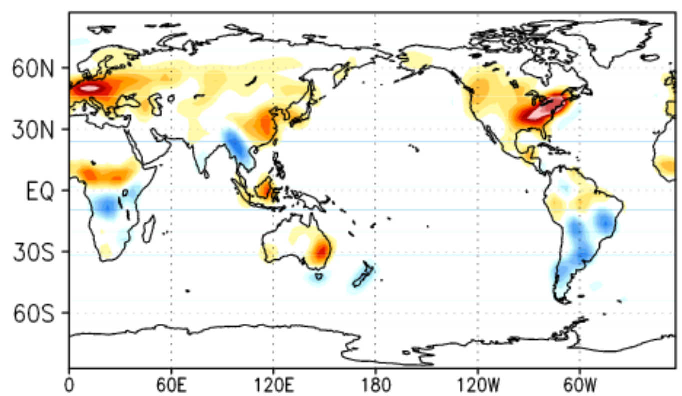
00Z01AUG ▶
After seven months of DA

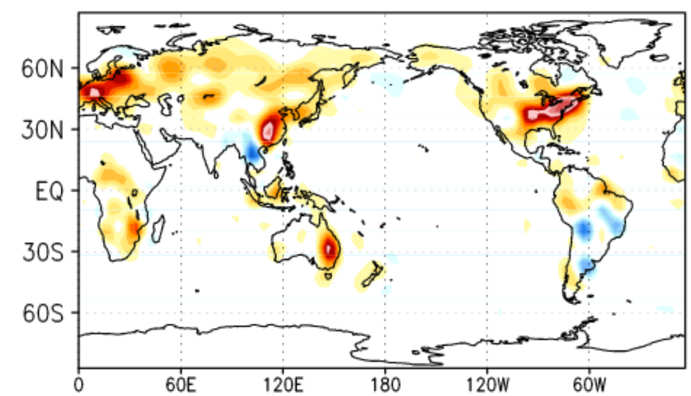




We succeeded in estimating time-evolving CF at model-grid scale

00Z01JAN ▶
After one year of DA





SUMMARY

- Future applications of EnKF-based data assimilation for improving both weather and climate prediction
  - 1) Combine model forecast and observations to create the best initial conditions ✓
  - 2) Improve observations ✓
  - 3) Improve models (both by parameter estimation ✓ and by using the analysis increments to correct the model ✓)
  - 4) Do strongly coupled data assimilation ✓